Science of the Total Environment 633 (2018) 571–592

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Spatially distributed potential evapotranspiration modeling and climate projections

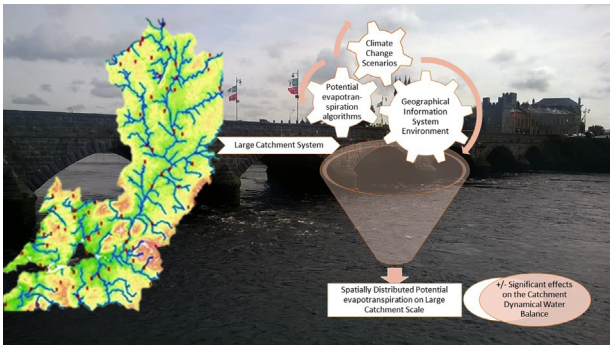
Salem S. Gharbia [a,*], Trevor Smullen [b], Laurence Gill [b], Paul Johnston [b], Francesco Pilla [a]

[a] Department of Planning and Environmental Policy, University College Dublin (UCD), Dublin, Ireland
[b] Department of Civil, Structural and Environmental Engineering, Trinity College, Dublin, Ireland

HIGHLIGHTS

- Empirical models well simulate spatially distributed potential evapotranspiration.
- All the simulated scenarios predicted an increase in potential evapotranspiration.
- A clear variation in potential evapotranspiration is visible in the coastal areas.
- Climate change has significant impacts on the future potential evapotranspiration.

GRAPHICAL ABSTRACT


Climate Change Scenarios
Potential evapotranspiration algorithms
Geographical Information System Environment
Large Catchment System
Spatially Distributed Potential evapotranspiration on Large Catchment Scale
+/- Significant effects on the Catchment Dynamical Water Balance

ARTICLE INFO

Article history:
Received 21 December 2017
Received in revised form 1 March 2018
Accepted 18 March 2018
Available online 28 March 2018

Editor: P. Kassomenos

Keywords:
GIS
Evapotranspiration
Geospatial-statistical
Algorithm

ABSTRACT

Evapotranspiration integrates energy and mass transfer between the Earth's surface and atmosphere and is the most active mechanism linking the atmosphere, hydrosphsophere, lithosphere and biosphere. This study focuses on the fine resolution modeling and projection of spatially distributed potential evapotranspiration on the large catchment scale as response to climate change. Six potential evapotranspiration designed algorithms, systematically selected based on a structured criteria and data availability, have been applied and then validated to long-term mean monthly data for the Shannon River catchment with a 50 m^2 cell size. The best validated algorithm was therefore applied to evaluate the possible effect of future climate change on potential evapotranspiration rates. Spatially distributed potential evapotranspiration projections have been modeled based on climate change projections from multi-GCM ensembles for three future time intervals (2020, 2050 and 2080) using a range of different Representative Concentration Pathways producing four scenarios for each time interval. Finally, seasonal results have been compared to baseline results to evaluate the impact of climate change on the potential evapotranspiration and therefor on the catchment dynamical water balance. The results present evidence that the modeled climate change scenarios would have a significant impact on the future potential evapotranspiration rates. All the simulated scenarios predicted an increase in potential evapotranspiration for each modeled future time interval, which would significantly affect the dynamical catchment water balance. This study addresses the gap in the literature of using GIS-based algorithms to model fine-scale spatially distributed potential evapotranspiration on the large catchment systems based on climatological observations and simulations in different climatological zones. Providing fine-scale potential evapotranspiration data is very crucial to assess the dynamical catchment water balance to setup management scenarios for the water abstractions. This study illustrates a transferable systematic method to design GIS-based algorithms to simulate spatially distributed potential evapotranspiration on the large catchment systems.
© 2018 Elsevier B.V. All rights reserved.

* Corresponding author.
E-mail address: salem.gharbia@ucd.ie (S.S. Gharbia).

https://doi.org/10.1016/j.scitotenv.2018.03.208
0048-9697/© 2018 Elsevier B.V. All rights reserved.

1. Introduction

After precipitation, evapotranspiration is the largest component of the terrestrial hydrological budget and thus critical for water resources evaluation and sustainable water management policies (Liu and Phinn, 2003; Portugali et al., 1994; Wu, 2002). Evapotranspiration is responsible for transferring moisture from the earth's surface to the atmosphere in vapor form. Due to complex interactions between meteorological and site-specific factors, evapotranspiration is extremely difficult to quantify. Water balance modeling requires the spatial estimation of potential evapotranspiration (PETS) throughout the catchment; that is the evapotranspiration, which would occur under optimal conditions. Evapotranspiration includes two processes that occur simultaneously in the soil-plant-atmosphere system, direct evaporation of moisture from the Earth's surface, and the exchange of water vapor, which occurs within the leaves of plants (transpiration) (Swenson and Wahr, 2006; Wilson et al., 2001). Evapotranspiration has long been recognized as a central process in the hydrological cycle (Penman, 1948; Rosenzweig, 1968; Holdridge, 1959; Gordon, 1998). The term potential evapotranspiration represents the ET, which would occur under optimal conditions where evapotranspiration is not limited by factors such as soil moisture. Evapotranspiration represents the most active of land-based hydrological processes, with approximately 65% of precipitation being evaporated and transpired (Kite and Droogers, 2000; Shukla and Mintz, 1982). Evapotranspiration fulfills numerous roles throughout its cycle. It accomplishes energy (heat) and mass (water vapor) transfer between the Earth's surface and atmosphere, and is the most active mechanism connecting the atmosphere, hydrosphsophere, lithosphere and biosphere (Zhao et al., 2004; Kite and Droogers, 2000; Zhang et al., 2001). Evapotranspiration is not only responsible for modulating atmospheric moisture but also temperature. Therefore, it can be seen that this process provides a vital link between the climatic, hydrological and ecological systems. Potential evapotranspiration remains one of the least satisfactorily explained processes in the hydrological cycle, principally because of its spatial variability (Andréassian, 2004; Andréassian et al., 2004; Oudin et al., 2005).

Due to the complexity and difficulties faced in the measurement of PETS, it is predominately estimated using formulae and observed meteorological data. There exists a vast number of models for estimating PETS, which may be grouped into several categories such as radiation, water budget, mass transfer, temperature, and combination methods. These methods vary greatly in terms of complexity, data requirements, and reliability.

Developing a GIS tool for modeling spatially distributed PETS from an undefined number of meteorological stations from monthly data of precipitation and temperature is the main objective of this paper. This tool provides the user with the PETS results on a seasonal and annual basis as well as an option to calculate values on a monthly frequency. The PETS GIS tool is presented using many methods with the ability to calibrate and validate the results. This study presents the primary results of the calculated PETS for both the baseline period and the future periods, based on climate change projections, for the Shannon River catchment in Ireland (Gharbia et al., 2016d; Gharbia et al., 2016b; Gharbia et al., 2015b; Gharbia et al., 2016a; Gharbia et al., 2015a). The River Shannon catchment, the focus of this study, is the largest transboundary river system and catchment in the island of Ireland and one of the most important water and power resources in the Republic of Ireland, see Fig. 1. Met Éireann, the Irish National Meteorological Service, calculates daily estimates of PETS at 25 synoptic weather stations throughout Ireland using the FAO Penman-Monteith method, 4 of which are located within the Shannon River catchment. As the catchment covers in excess of 18,000 km^2, it is evident that 4-point estimates are not sufficient to estimate spatially distributed PETS. The Penman-Monteith method is widely considered as a standard method for the calculation of PETS. However, its application, particularly for this large catchment, is questionable due to the need for specific data for a variety of

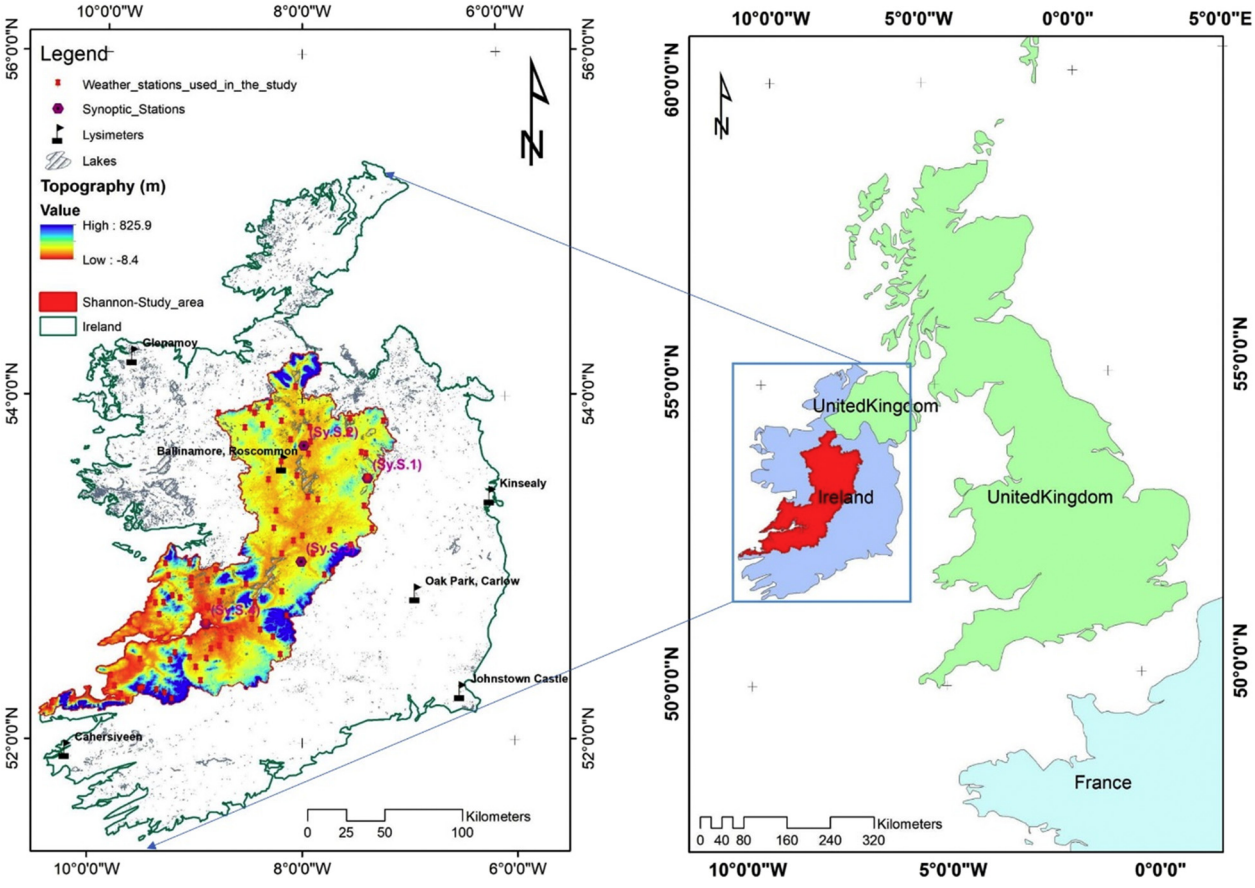


Fig. 1. Location map for the Shannon River catchment.

Table 1
PETS models rating. (A) number of climatological datasets required. (B) the spatial availability of required data. (C) the number of computations required. (D) suitability for use within a GIS platform. (Total) the cumulative rating.

Method	Category	(A)	(B)	(C)	(D)	(Total)
Priestley-Taylor	Radiation	3	3	2	3	11
Makkink	Radiation	3	3	1	3	10
Hargreaves & Samni	Temperature	1	1	2	1	5
Blaney Criddle	Temperature	1	1	1	1	4
Hargreaves	Temperature	1	1	2	1	5
Thornwhite	Temperature	1	1	3	2	7
Linacre	Temperature	1	1	1	1	4
Rohwer	Mass transfer	3	3	1	1	8
Penman-Monteith	Mass transfer	3	3	3	3	12

parameters, which are only available from a limited number of locations and will result in interpolation of data from distant meteorological stations. As a result, less data intensive empirical models are often utilized which allows for data from a greater number of meteorological stations to be used thus resulting in more spatially representative estimates. This study is addressing the gap in the literature of using GIS-based algorithms to calculate the fine scale spatially distributed PETS on the large catchment systems based on climatological observations and simulations.

2. Materials and methods

2.1. Evaluating and choosing models to quantify PETS

The reliability of PETS estimates depends upon the number of stations from which data is obtained and the number of years of available data (Chattopadhyay and Hulme, 1997), as more stations gives more accurate spatially distributed PETS, based on the used spatial interpolation method the minimum number of needed stations can statistically be calculated which is not available in reality in most of the cases. As a result, numerous authors such as (Xu and Singh, 2002; Fennessey and Vogel, 1996; Chattopadhyay and Hulme, 1997; Oudin et al., 2005; Kite and Droogers, 2000) among many others, recommend that more simplified methods be used when only a limited number of meteorological stations are available with the required data.

Studies have focused on developing methods to accurately estimate PETS and improve on existing methods for over 70 years. In that time, numerous studies of varying scope have been completed to determine the most suitable model to be used to estimate PETS for varying purposes. (Jensen et al., 1990) evaluated 20 formulae for estimating PETS versus lysimeter data from around the world. He concluded that the Penman-Monteith method was the best method, while the performance of the remainder varied depending on calibration and local conditions. As discussed previously, methods are most suited to the environment in which they were developed.

In evaluating models to estimate PETS it is also necessary to consider what the requirements are for the calculated values. For instance, (Oudin et al., 2005) compared the performance of 27 PETS models over 308 catchments to find the most relevant for rainfall-runoff models. It was found that temperature and radiation based methods performed best and are as efficient as models that are far more complex. Kay and Davies (2008) investigated the performance of a simple temperature based formula proposed by (Oudin et al., 2005) compared to that of the Penman-Monteith method. PETS estimates using both methods were compared to that of the UK meteorological office's PETS values for a 30-year period 1961–1990. It was found that the much simpler temperature based method generally gave better estimates of PETS than the Penman-Monteith method. This supports the opinion of many

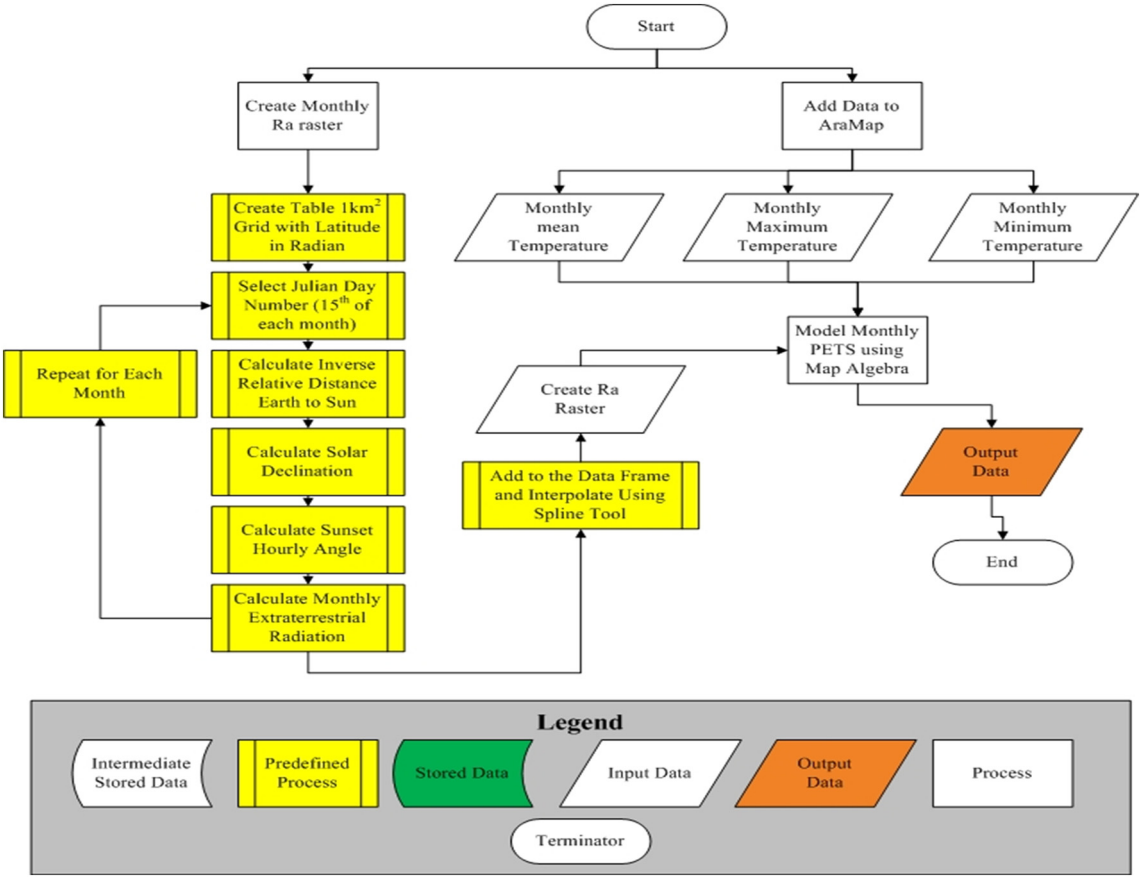


Fig. 2. Hargreaves and Samani designed algorithm flowchart.

authors who consider more simple models, once locally calibrated, to be as effective as more complex models (Xu and Singh, 2002; Fennessey and Vogel, 1996; Chattopadhyay and Hulme, 1997; Oudin et al., 2005; Kite and Droogers, 2000).

CGIAR-CSI (2007) spatially estimated PETS using 4 temperature-based models (Droogers and Allen, 2002; Hargreaves and Samani, 1985; Holland, 1978; Thornthwaite, 1948). The results for each were compared to PETS values at 2288 meteorological stations in South America and South Africa. Based on the results, the Hargreaves & Samani method was chosen as the most suitable to model PETS globally. The Hargreaves model was found to perform almost as well the Penman-Monteith method but required far less parameterisation with significantly less sensitivity to error in climate inputs.

The most comprehensive research on available PETS formulae has been completed by Xu and Singh who commenced a research programme in 1996. Their first paper investigated thirteen equations based on the mass- transfer method; these equations were expressed in seven generalized equations (Singh and Xu, 1997). The seven generalized equations were then compared with pan evaporation results at four climatological stations in north-western Ontario, Canada. All of the formulae yielded satisfactory estimates for monthly PETS. As discussed previously, model parameters were required to be calibrated using local meteorological variables.

Xu and Singh (2000) then evaluated five radiation based PETS formulae (Abtew, Hargreaves, Makkink, Priestley-Taylor and Turc), which were compared with pan evaporation measured at Changing station in Switzerland (Turc, 1961; De Bruin, 1983; Makkink, 1957; Hargreaves and Samani, 1982; Abtew, 1996; Xu and Singh, 2000). The evaluation and comparison process were first completed using original empirical constants and then using recalibrated constant values. Using original values, the Abtew formula was found to give reasonable estimates of PETS while the remainder demonstrated large errors. With recalibrated constants, a significant improvement was found in four out of the five methods. The Makkink and Priestley-Taylor formulae were concluded to be the best methods for use in the study region. Xu and Singh (2001) also evaluated and compared seven temperature-based formulae (Thornthwaite, Linacre, Blaney-Criddle, Hargreaves, Kharrufa, Hamon, Romanenko) with data from two climatological stations (Rawson Lake and Atikokan) in north-western Ontario, Canada. Similar to the foregoing study comparisons were made using both original and recalibrated constant values (Romanenko, 1973; Hamon, 1961; Kharrufa, 1985; Blaney and Criddle, 1964; Linacre, 1977; Xu and Singh, 2001; Hargreaves and Samani, 1982; Thornthwaite, 1948). Using original constants, the Blaney-Criddle equation resulted in mean seasonal evaporation values that agreed most closely with pan evaporation values, while the remainder demonstrated large errors. With recalibrated constant values, all seven methods provided reasonable results. With properly determined constant values, the Blaney–Criddle, Hargreaves and Thornthwaite methods were concluded to be the best temperature based methods for the study area. Based on the results of the foregoing studies Xu and Singh (2002) selected the best methods from each of the three categories: (i) mass-transfer based methods, (ii) radiation based methods, and (iii) temperature-based methods. A cross comparison of the best formulae selected from each category

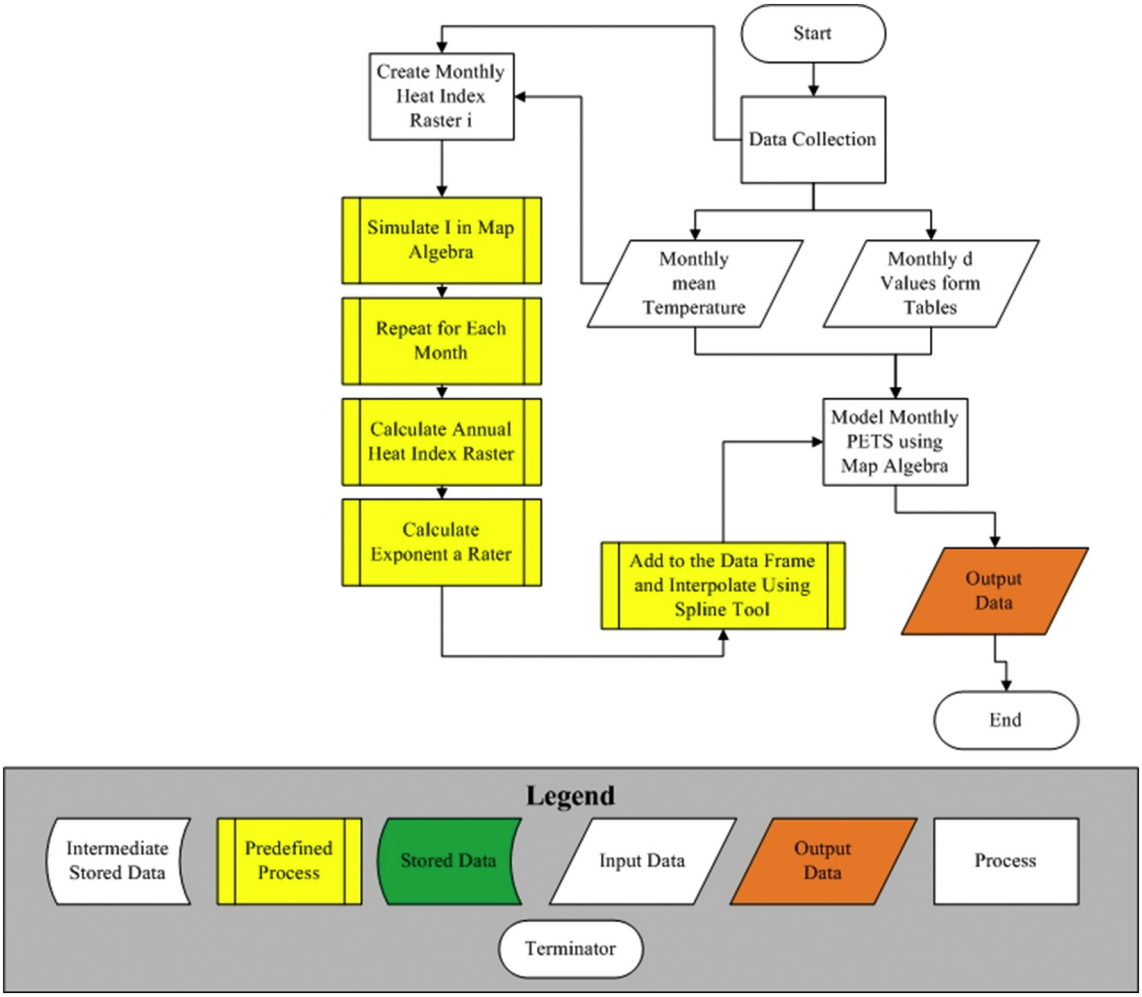


Fig. 3. Thornthwaite designed algorithm flowchart.

was made. Five PETS formulae (Hargreaves and Blaney-Criddle (temperature-based), Makkink and Priestley-Taylor (radiation-based) and Rohwer (mass-transfer-based)) were evaluated and compared with PETS values calculated using the Penman-Monteith method using daily meteorological data from the Changing station in Switzerland for the 5-year period 1990–1994. The calculations of the Penman-Monteith equation followed the procedure recommended by FAO (Allen, 2000). Both original and recalibrated constant values were used. With original constant values, all except the Blaney-Criddle method returned reasonably similar results to the Penman-Monteith method. Significant improvement was achieved for the Blaney-Criddle method by recalibrating constants and adding a transition period in determining the parameter k. Constant values were also recalibrated for the remaining methods. It was concluded from the study that, using locally determined parameter values, all five empirical methods gave acceptable estimates of PETS. The methods were ranked as follows:

1. Priestley-Taylor (Radiation-based).
2. Makkink (Radiation-based).
3. Hargreaves (temperature-based).
4. Blaney-Criddle (temperature-based).
5. Rohwer (Mass-transfer).
6. Penman-Monteith.

This ranking gives a very useful insight of which method can be recommended to be used in calculating evapotranspiration based on the data availability. It was also concluded that the differences in performance between the best methods selected from each category are smaller than the differences between the different methods within each category as reported in earlier studies.

As mentioned, empirical PETS formulae are typically developed using site-specific data and experiments, thus their performance will vary depending on location and local conditions. Although calibration of empirical constants with local data will maximize a given formula's performance for local conditions, the performance relative to other methods will continue to vary. Therefore, from the aforementioned comparative studies, all of which were completed outside of Ireland, it is not possible to identify the method most suited for use in Irish conditions. It is possible to identify the continuously best-performing methods and those which would be best suited for use in this study.

From a review of available literature, eight PETS models were selected, as listed in Table 1. These methods were selected as they are the generally best performing methods and those which are most suited to spatially estimate PETS within a GIS platform.

In order to further evaluate the chosen methods, four criteria were chosen by which to evaluate their suitability. Under each of the criteria, each method receives a rating between 1 and 3. The three methods with

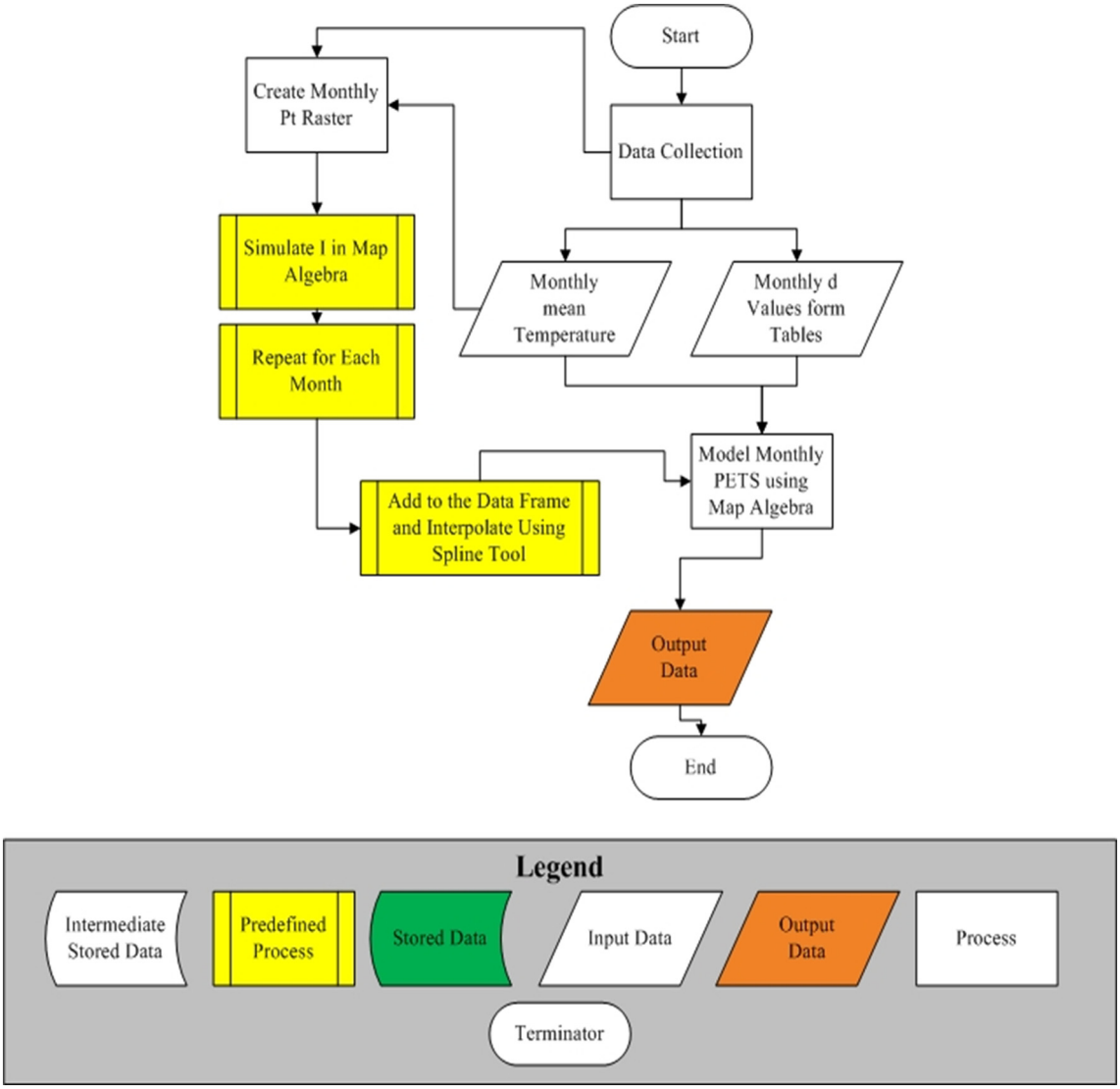


Fig. 4. Hamon designed algorithm flowchart.

the lowest cumulative rating will be selected for further evaluation with local data and subject to the data availability.

The evaluation criteria were as follows:

A. The number of climatological datasets required e.g. Temperature, wind speed etc. Ratings for this criterion are as follows: 1 dataset = 1; 2 datasets = 2; 3+ datasets = 3.
B. The spatial availability of required data. Ratings for this criterion are as follows: temperature, precipitation = 1; wind speed = 2; Radiation, vapor pressure, atmospheric pressure = 3.
C. The number of computations required, which can be illustrated by the amount of map algebra functions that needed to complete the PETS calculation for a single pixel of the catchment within the GIS environment. The complexity of available empirical PETS models varies greatly from relatively simple methods requiring an evaluation of a single formula to those, which would require an evaluation of several formulae prior to application of a formula to estimate PETS. Ratings for this criterion are as follows: 1 computation = 1; 2 computations = 2; 3+ computations = 3.
D. Suitability for use within a GIS platform. Ratings for this criterion are as follows: Easily applied = 1; moderate = 2; difficult to apply = 3.

From the application of the rating procedure, four PETS models were identified as being the most suitable (Hargreaves & Samani, Blaney-Criddle, Hargreaves, Linacre), which were taken to further assessment regarding the data availability and the suitability for the study area.

In order to run the PETS simulation using the evaluated methods, it was the intention to use lysimeter data from a trusted device, lysimeter that has been continuously validated by the water budget equation, to calibrate the chosen empirical equations for local conditions. While reviewing the data sources in Ireland, it was found that three lysimeters were operated by Met Éireann, as reported on Met Éireann's website. However, it transpired that only one lysimeter is maintained by Met Éireann, which is located on Valentia Island. Due to its location on a small island in the Atlantic Ocean data from the lysimeter would not be representative of the Shannon River Basin District. The remaining two locations were found to be operated by Teagasc, The Agriculture and Food Development Authority, and we could not access this data.

Because of the absence of reliable PETS data with which those evaluated methods previously shortlisted may be calibrated it was not possible to calibrate nor identify the most appropriate method for use within the Shannon River Basin District. As it was not possible to recalibrate the selected models for local conditions and thus identify the best performing model for application within the GIS, a number of models were selected for the application. In order to evaluate the performance of the model, short-term monthly data was sourced from Met Éireann. This data consisted of mean monthly values of PETS for four synoptic weather stations within the Shannon, the PETS values were calculated by Met Éireann by Penman-Monteith using the full range of required input data for the four-point locations, this data was compared with the calculated results from PETS models as an evaluation step.

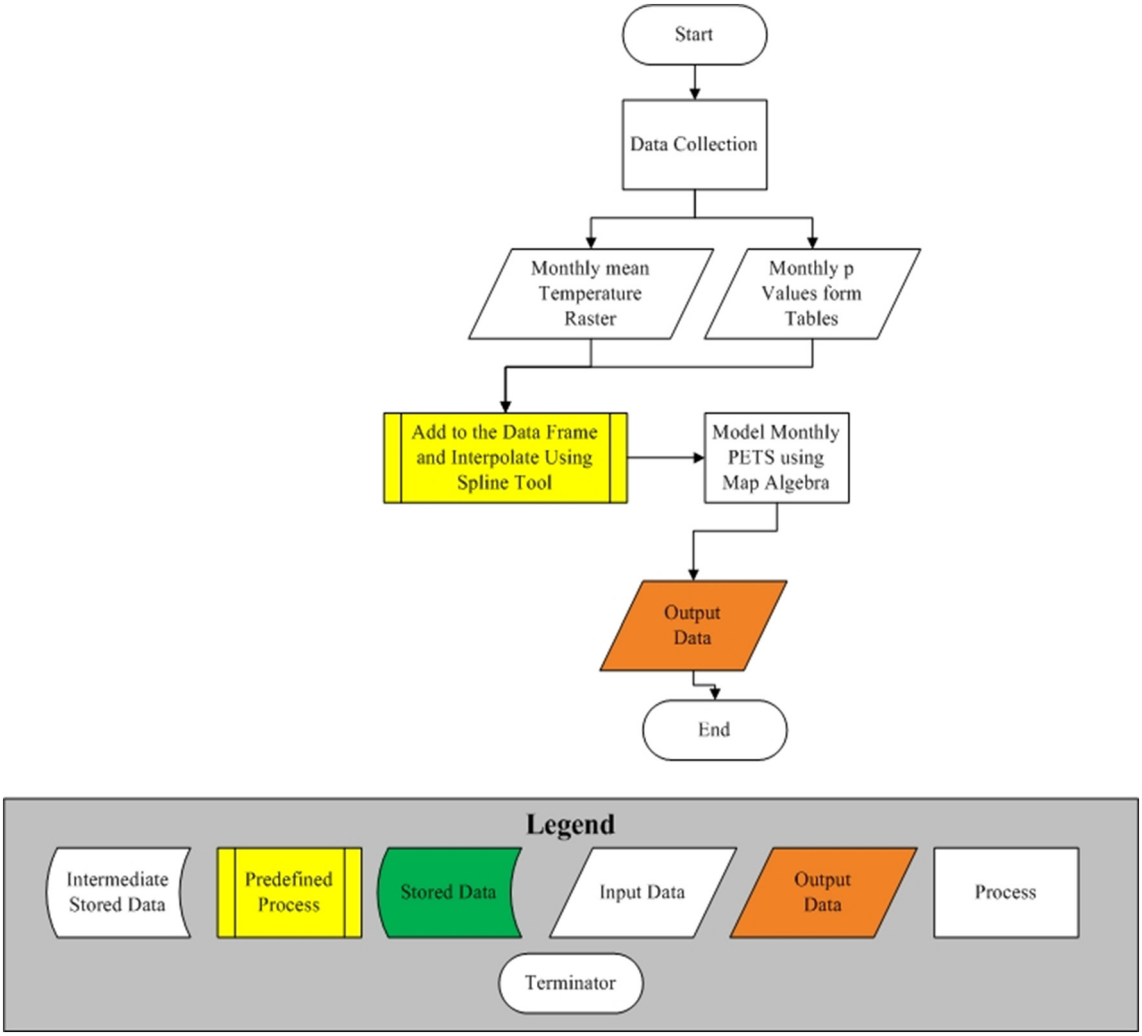


Fig. 5. Blaney-Criddle and Kharrufa designed algorithm flowchart.

As discussed previously, because of the absence of lysimeter PETS data it was not possible to complete a comparative recalibration of the PETS models shortlisted. This study aimed to produce a GIS tool to simulate PETS using different simulation methods, this tool used six methods for spatially distributed PETS modeling as follow:

- Blaney-Criddle (Allen and Pruitt, 1986).

The Blaney-Criddle (1950) method for estimating PETS is most well known in the U.S.A, but it has been used extensively elsewhere. For example, the FAO temperature methodology recommended by (Pruitt and Doorenbos, 1977) is based on the Blaney-Criddle method. Although initially used for estimating the consumptive use of irrigated crops in the western United States, it is uniformly applicable for estimating PETS in agricultural lands or catchments with reasonably uniform vegetation. The common form of the Blaney-Criddle equation is:

$$PETS = Kp(0.46\,T_A + 8.13) \quad (1)$$

where PETS is evapotranspiration in mm from a reference crop for the period in which p is expressed, Ta is the mean temperature in °C for the same period, p represents the percentage of total daytime hours for the period used (whether daily, weekly, monthly etc.) out of total daytime hours of the year, i.e. 365 × 12, and k is a monthly consumptive use coefficient (Pruitt and Doorenbos, 1977), depending on vegetation type, location and season.

Blaney-Criddle recognized that temperature has one of the greatest influences on ET rates and that records are far more uniformly available than other factors. Furthermore, sunshine hours were also identified as a noteworthy factor in the rate at which plants grow and consume water. However, sunshine records are not usually available thus Blaney-Criddle recommended the use of tables of theoretical sunshine hours for different latitudes in the absence of actual data.

- Kharrufa (Kharrufa, 1985).

Kharrufa (1985) derived a relatively simple equation similar to that of Blaney-Criddle described previously with which PETS may be calculated. PETS is calculated based on a relationship between temperature and sunshine duration and is given by:

$$PETS = 0.34\,P\,T_A^{1.3} \quad (2)$$

where PETS is evapotranspiration in mm/month and p and Ta has the same definitions as that given previously.

- Hargreaves and Samani (Hargreaves and Samani, 1982).

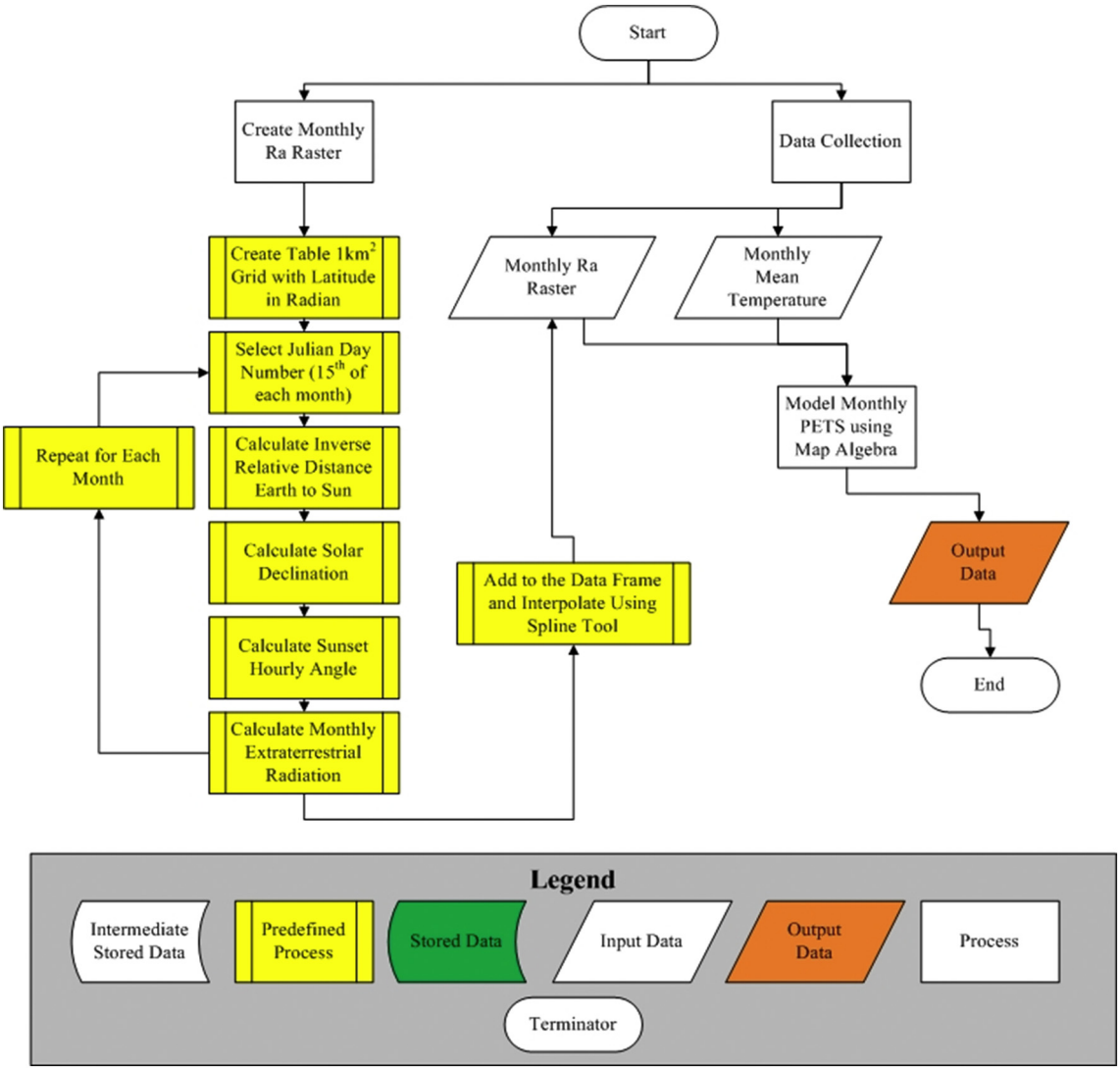


Fig. 6. Oudin designed algorithm flowchart.

Table 2
Synoptic meteorological stations within the Shannon River Basin District.

Location	Elevation (meter above mean sea level)	Percentage of valid data (%)
Mullingar	101	88
Mount Dillon	39	84
Gurteen College	75	87
Shannon Airport	6	97

Hargreaves (1975) published an empirical equation for estimating PETS which was developed using data from a precision lysimeter and weather data for an 8-year period. It was found for a 5-day time step that 94% of the variance in measured versus modeled values was explained through average temperature and solar radiation. The portion of extra-terrestrial solar radiation which penetrates through clouds and reaches the earth's surface is the primary heat source for ET processes. Subsequent studies by Hargreaves and Samani (1982) showed solar radiation may be estimated from the difference between maximum and minimum temperature (Hargreaves and Samani, 1982). This is possible as under clear skies incoming solar radiation may pass freely through the atmosphere resulting in high temperatures while at night temperatures are low due to outgoing longwave radiation (Allen et al., 1998). Contrastingly under cloudy conditions a fraction of the incoming solar radiation is prevented from reaching earth thus resulting in lower temperatures, while at night temperatures are higher as cloud cover limits outgoing longwave radiation. As solar radiation data is frequently unavailable Hargreaves and Samani recommended estimating it from extra-terrestrial radiation and minimum and maximum temperature. Based on their previous studies Hargreaves and Samani (1985) presented a simplified equation, which requires only temperature, the day of the year and latitude.

$$PETS = 0.0135K_{RS}(RA/\lambda)\,(Tmax - Tmin)^{0.5} * (TA + 17.8) \quad (3)$$

where PETS is the monthly evapotranspiration rate in mm, KRs is an empirical radiation adjustment coefficient, λ is the latent heat of vaporization in MJ/kg, for the mean air temperature commonly assumed to equal 2.45 MJ/kg, RA is the extra-terrestrial solar radiation in MJ/m^2/month. Tmax and Tmin are monthly maximum and minimum monthly temperature in °C, the constant 0.0135 is a factor to convert from empirical US units to the international system of metric units. TA is the mean temperature in °C.

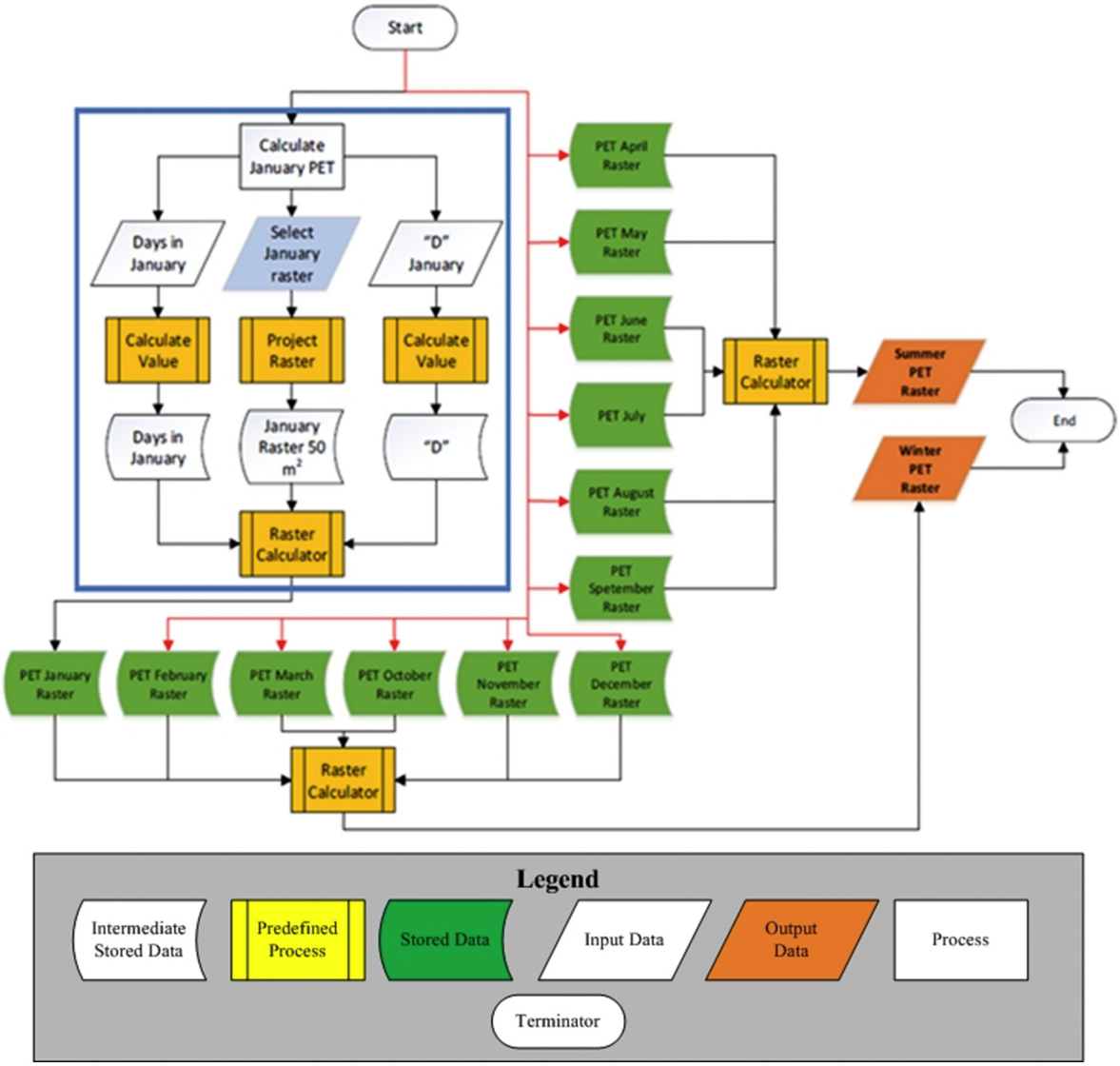


Fig. 7. PETS projection designed algorithm flowchart.

• Oudin (Oudin et al., 2010).

(Oudin et al., 2005) examined the efficiency of 27 PETS models over a large sample of 308 catchments which were located in France, Australia, and the USA. It was found that models based upon temperature and solar radiation performed best. Oudin selected two of the best performing models (Jensen-Haise and McGuinness) both of which had the same generalized form (Parmele and McGuinness, 1974; McGuinness and Bordne, 1972). Oudin then calibrated his formula over the catchments and produced a common formula given by:

$$PETS = \frac{RA}{\lambda\rho}\frac{Ta}{100} \quad (4)$$

where PETS is monthly potential evapotranspiration in mm and ρ is the relative density of water which = 1, λ is the latent heat of vaporization in MJ/kg, RA is the extra-terrestrial solar radiation in MJ/m^2/month, Ta is the mean temperature in °C.

The equation relies on expected solar radiation as calculated from Julian day and latitude and not actual measured data; thus, the only real independent variable is temperature. Therefore, the Oudin equation, similar to the Hargreaves and Samani method discussed previously, is referred to as a temperature based method although it has a strong dependency on solar radiation.

• Thornthwaite (Thornthwaite and Mather, 1957)

Thornthwaite (1948) developed a methodology to estimate evapotranspiration for short vegetation. This is a widely used method which was derived by correlating values of mean monthly temperature with that of evapotranspiration for valleys where sufficient soil moisture was always available to sustain active transpiration (Thornthwaite, 1948). The Thornthwaite method determines values of PETS using values of observed air temperature and duration of sunlight data, the rationale being that air temperature acts as a proxy to net radiation. The determination of monthly PETS involves a number of computational steps as follows:

$$PETS' = C\left(\frac{10Ta}{I}\right)^{a} \quad (5)$$

where PETS' is the unadjusted monthly potential evapotranspiration in mm, C is a constant = 16, I is the annual heat index given by Eq. (7), and *a* is an empirical exponent given by Eqs. (7) and (8). The annual value of the heat index I is calculated by summing monthly indices over a 12-month period. The monthly indices are obtained from the equation:

$$i = \frac{Ta^{1.51}}{5} \quad (6)$$

The yearly heat index in calculated by:

$$I = \sum_{1}^{12} i_j \quad (7)$$

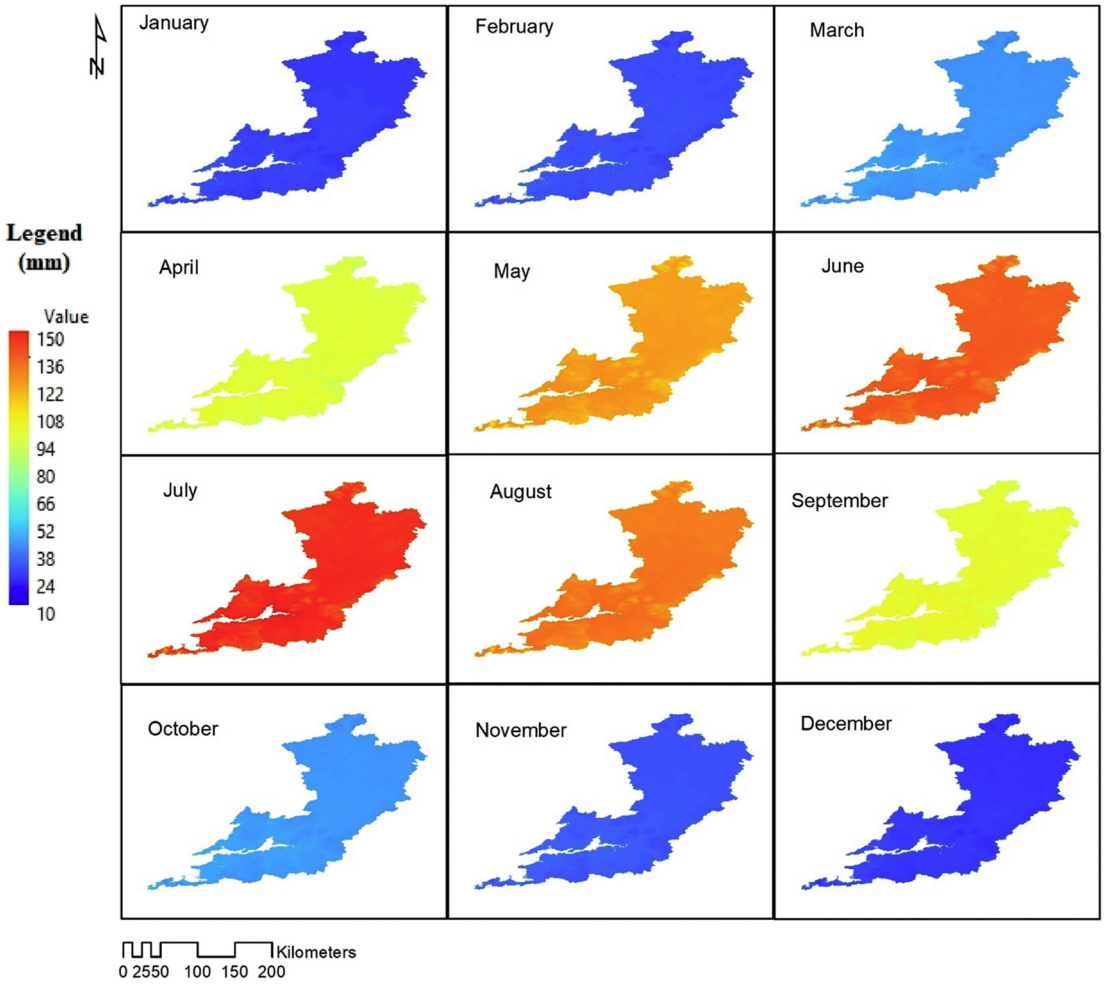


Fig. 8. Blaney-Criddle baseline monthly PETS raster maps.

The exponent *a* is calculated by:

$$\alpha = (67.5 \times 10{-}8\ I3){-}(77.1 \times 10{-}6\ I\ 2) + (0.0179\ I) + 0.492 \quad (8)$$

PETS' which is calculated using Eq. (5) is an unadjusted monthly value of PETS for a standard month with 30 days with 12 h/day of sunlight. These PETS' values were adjusted depending on the number of days in a month and the duration of average monthly daylight which is a function of season and latitude. This process for any month is given by:

$$PETS = PET' \frac{d}{12}\left(\frac{N}{30}\right) \quad (9)$$

where PETS is the adjusted monthly potential evapotranspiration in mm, d is the duration of average monthly daylight in hours, and N is the number of days in a given month (1–31 days).

- Hamon (Hamon, 1961)

Hamon (1961) formulated a simplified expression to estimate PETS. The method proposed by Hamon is most commonly used for monthly, seasonally or yearly estimates of PETS. The Hamon method estimates PETS given mean air temperature and day length data. The Hamon method has been employed globally for hydrological studies where only temperature data is available (Hamon, 1961). The simplified equation proposed by Hamon is given by:

$$PETS = 0.55\ D^2\ Pt \quad (10)$$

where PETS is the monthly potential evapotranspiration in mm, D is the hours of daylight for a given month in units of 12 h [hr/12 h] and Pt is a saturated water vapor density term calculated by:

$$Pt = \frac{4.95\ e^{0062Ta}}{100} \quad (11)$$

This method was developed based on the relationship between PETS, maximum possible radiant energy and moisture-holding capacity of the air at the prevailing air temperature. Hamon determined the constant value of 0.55 through comparison of results from the far more complex Thornthwaite method discussed previously. Sunlight hours are used as a proxy for incoming radiant energy while Pt is used as a proxy for moisture-holding capacity of the air. It's worth mentioning that Solar Radiation would be a better representation of both daylight and sunlight hours as solar radiation considers the cloud covers, however the Hamon method got developed, calibrated and validated using the daylight and sunlight hours parameters which helps in the cases of not availability of solar radiation data. Redeveloping Hamon method using solar radiation parameter would be a very interesting future research topic.

2.2. Data setup

In this paper, the required data is mainly climatological data for the baseline and four future scenarios. Multi-dimensional datasets for temperature, humidity, windspeed, precipitation and solar radiation, all with minimum, mean and maximum values, for the Shannon River

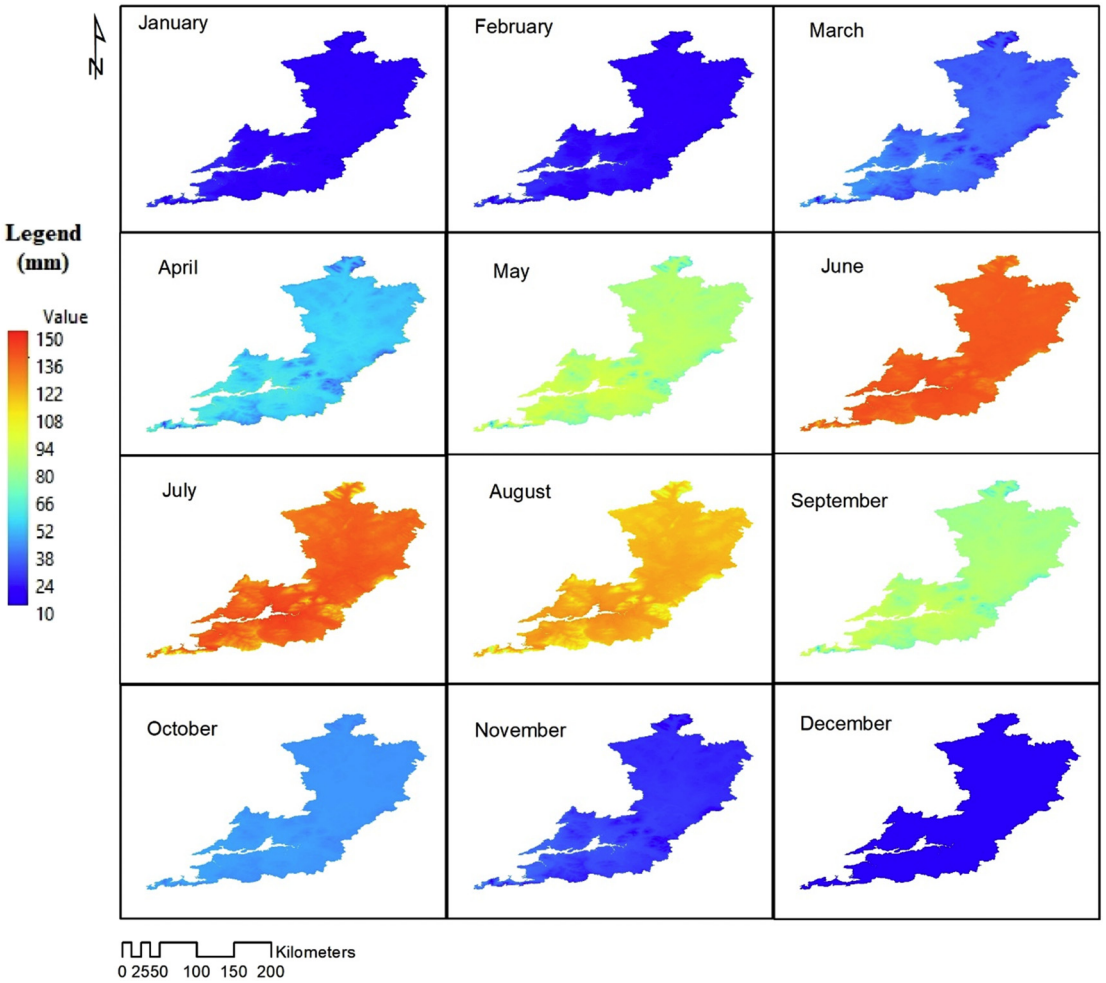


Fig. 9. Kharrufa baseline monthly PETS raster maps.

catchment were obtained from (Gharbia et al., 2016b; Gharbia et al., 2016c). Climate change projections for the Shannon River Basin District were obtained for several climate variables from Gharbia et al. (2016b), including mean monthly temperature, from multi-GCM ensembles for three future time intervals (2020, 2050 and 2080) using a range of different Representative Concentration Pathways (RCPs). The climate change models were based upon two different RCPs; using a radiative forcing of 4.5 W/m^2 and 8.5 W/m^2 respectively, which were produced from 50% (median) and 75% (3rd quartile) multi-GCM ensembles results.

In general, Gharbia et al. (2016b) simulations results show that temperature will increase every year, in particular RCP 8.5 (75%) has the highest increasing rate (1.85 °C in 2080 as an average over Shannon catchment), which is consistent with the global rise in air temperatures. Gharbia et al. (2016b) concluded that all seasons would have an increase in temperature with the highest increases occurring in the spring and summer. Trends in precipitation show greater regional variation than temperatures, with occasional conflicting trends from stations which are geographically relatively close. However, there is evidence of an increase in the quantity of precipitation with time in general except for RCP 4.5 (50%) values they are higher in 2050 than 2080 and that because of the different adapted parameters in the downscaled GCMs in that particular climate scenario. Gharbia et al. (2016b) shows that RCP 8.5 (75%) would predict the highest future precipitation quantities over the catchment. For solar radiation, all simulations indicate that there will be a significant increase in solar radiation over the Shannon catchment in the future, with such an incremental increase obvious when moving from RCP 4.5 (50%), RCP 4.5 (75%), RCP 8.5 (50%) to RCP 8.5 (75%), respectively. The relative humidity and wind speed simulation results indicate a fluctuation in values but with slight increases dominant over the Shannon catchment. Predicted increases relative humidity and wind speed are clear when moving from RCP 4.5 (50%), RCP 4.5 (75%), RCP 8.5 (50%) to RCP 8.5 (75%), respectively. There are significant increases in the relative humidity and wind speed for the 2050 and 2080 from the RCP4.5 (75%) and RCP8.5 (75%) projections.

Gharbia et al. (2016b) provides multidimensional climatological datasets and simulations for the Shannon River catchment based on four future scenarios RCP4.5(50%), RCP4.5(75%), RCP8.5(50%) and RCP8.5(75%). Thus, a significant quantity of climatological data was required to produce long-term mean monthly estimates of PETS within the Shannon River Basin District. The data source for all the baseline weather data was obtained from Met Éireann, the Irish National Meteorological Service.

Met Éireann is the leading provider of weather information and related services for Ireland. Observed daily data for temperature was obtained from all available stations (96 stations) in the Shannon River Basin District for the period 1961–2014. The majority of stations from which data was received can be considered low lying and of high quality. Baseline mean monthly temperature was calculated for the period 1961–2000, with the remainder reserved for calibration and evaluation processes. These data was processed within ArcGIS and a long-term mean monthly temperature raster was produced for each month. As discussed previously, throughout this study the Irish National Grid coordinate system and a 50 m^2 cell size were employed.

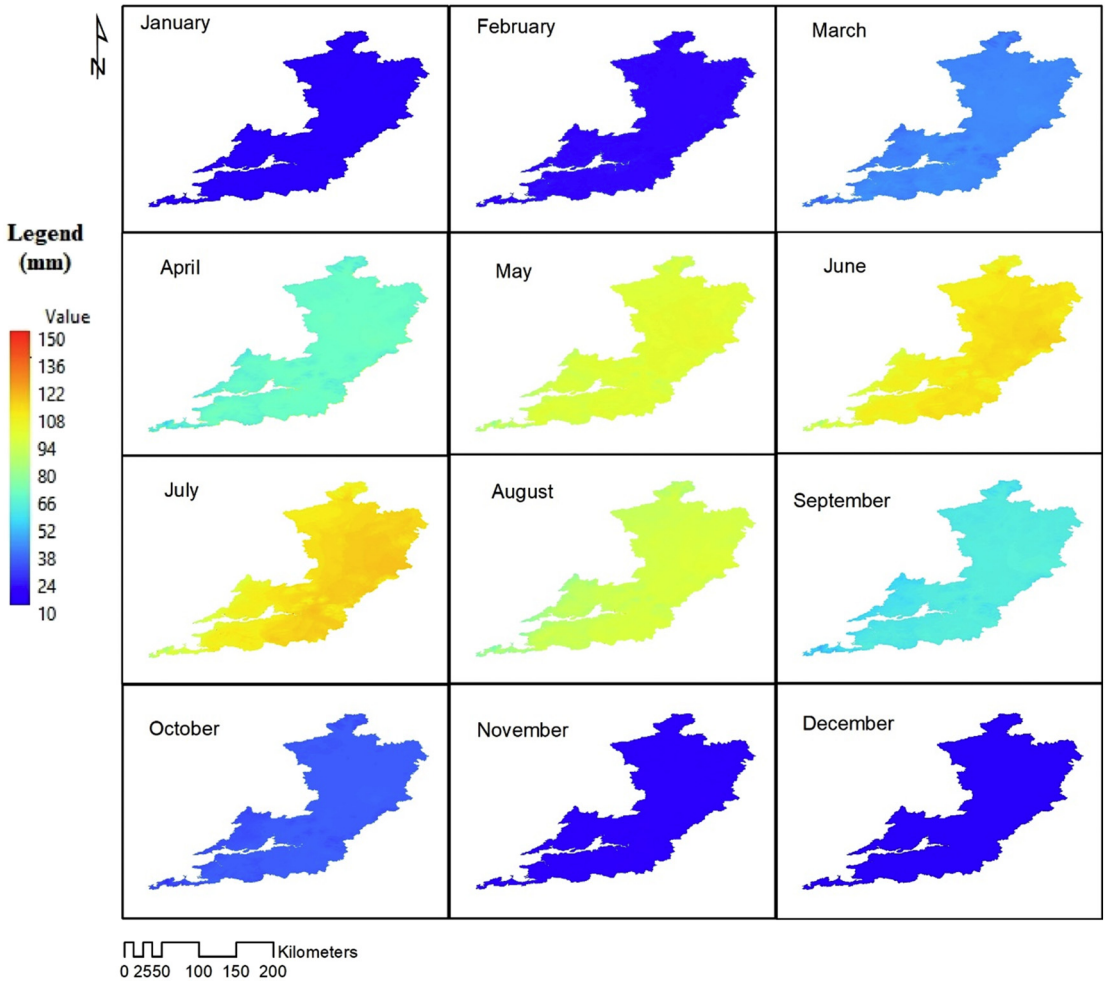


Fig. 10. Hargreaves and Samani baseline monthly PETS raster maps.

2.3. Design the PETS GIS-based algorithms

The methodology mainly depended on the design of the PETS GIS algorithms based on the methods illustrated in the previous sections. A validation and performance evaluation process was then implemented to get the best-performing temperature-based method in order to use it in the PETS projection simulations, which were based on climate change scenarios.

As discussed above, six methods were used in PETS modeling process using the designed flowcharts below, in some of these flowcharts the interpolation is used. As all the used methods are temperature based methods, and temperature as an atmospherically parameters is relatively smoothly spatially distributed parameter, and as the Shannon River catchment is relatively flat catchment without any really high mountains, so the Spline spatially interpolation method is used in all the methods.

- Hargreaves and Samani

The Hargreaves and Samani method was one of the most complex methods applied during this study. A flow chart of the methodology used in modeling PETS using this method is shown in Fig. 2, based on the spatially distributed calculation process for the previously discussed equations.

- Thornthwaite

The Thornthwaite method was completed using a similar methodology to the Hargreaves and Samani method using the designed algorithm flowchart illustrated in Fig. 3. Monthly heat index values *I*, previously illustrated, were estimated from mean monthly temperatures. A raster file of *i* was created for each month, and then summed to produce a raster file of *I*. Once *I* had been calculated it was possible to create a raster of exponent *a*, then produce the PETS monthly raster maps.

- Hamon

Similar to the preceding methods, the Hamon method required preprocessing to create monthly raster files of variable Pt. The designed algorithm flowchart for this method illustrated in Fig. 4.

- Blaney-Criddle and Kharrufa

The Blaney-Criddle and Kharrufa methods were among the simplest methods applied within this study. Their application required mean monthly temperature rasters and monthly values for p, once retrieved the methods could be readily applied within the ArcMap GIS environment. The designed algorithm flowchart for this method illustrated in Fig. 5. The represented flow chart in the Fig. 5 represents a practical simplification to the Eq. (1), as the two input parameters in the equation are prepared in the raster data format then they used in the map algebra processor in the ArcMap to make the PETS calculation according to the Eq. (1).

- Oudin

The Oudin method was similar in its application to the Hargreaves and Samani method described previously, requiring mean monthly temperature data and estimates of monthly extraterrestrial radiation as shown in Fig. 6.

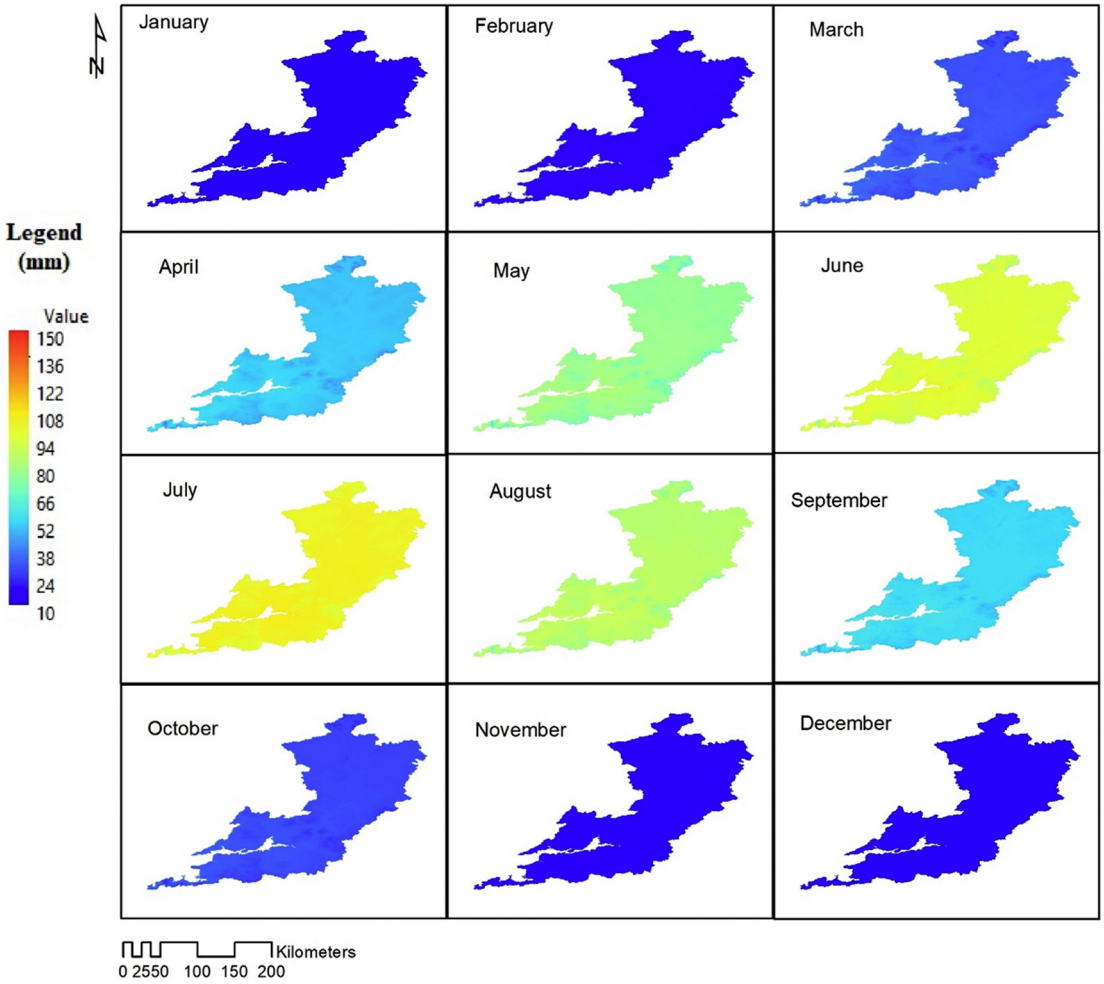


Fig. 11. Oudin baseline monthly PETS raster maps.

2.4. Validation and performance evaluation

Short-term (2012–2015) mean monthly PETS rates for four synoptic weather stations within the Shannon River Basin District were obtained from Met Éireann. The four synoptic stations are listed in Table 2 with their respective elevation and the percentage of the valid data, there locations are shown in Fig. 1. The resultant baseline mean monthly PETS values at the same location as the synoptic meteorological stations from each of the six selected models were compared with that of the short-term mean monthly PETS data from the Met Éireann stations (which are calculated by Penman-Monteith method). The evaluation of the performance of the PETS models was completed on both a graphical and statistical basis. The modeled values were evaluated based on a number of statistical values. Firstly, the coefficient of determination (R^2) was determined for each data set, which is a statistical measure of how close the data are fitted to the trusted data. Similarly, the root means square error (RMSE), which is a measure of the difference between modeled values and the trusted values was calculated. The mean absolute percentage error (MAPE), which is a measure of prediction error, in %, of the model was also calculated. Finally, the mean absolute deviation (MAD) was calculated, which measures the size of the error between the two sets of data.

2.5. Climate change effects on PETS

Upon assessment, it was found that the results from the Hamon method best correlated with the data available from the synoptic stations. In that regard, the Hamon method was selected for modeling changes in future PETS within the Shannon River Basin District as a consequence of climate change.

Climate change projections for the Shannon River Basin District were obtained for several climate variables from Gharbia et al. (2016b), including mean monthly temperature, from multi-GCM ensembles for three future time intervals (2020, 2050 and 2080) using a range of different Representative Concentration Pathways (RCPs). The climate change models were based upon two different RCPs; using a radiative forcing of 4.5 W/m^2 and 8.5 W/m^2 respectively, which were produced from 50% (median) and 75% (3rd quartile) multi-GCM ensembles simulation results.

The Hamon method was applied to three future time intervals each including four possible climate scenarios, each requiring PETS to be estimated for twelve months; thus, it was required for the Hamon method to be applied for 144 monthly scenarios. A methodology flowchart for the algorithm created under the GIS environment is shown in Fig. 7; where all processes encompassed in blue are applicable prior to all output rasters shown in green, simply Fig. 7 can be described as a loop for the Fig. 4 in order to get all the maps according to all the climate scenarios in monthly time step.

3. Results and discussions

3.1. Baseline PETS monthly simulation

The 6-selected empirical temperature based PETS formulae were applied to long-term mean monthly temperature data for the Shannon River Basin District within a GIS. For each approach, a raster map of

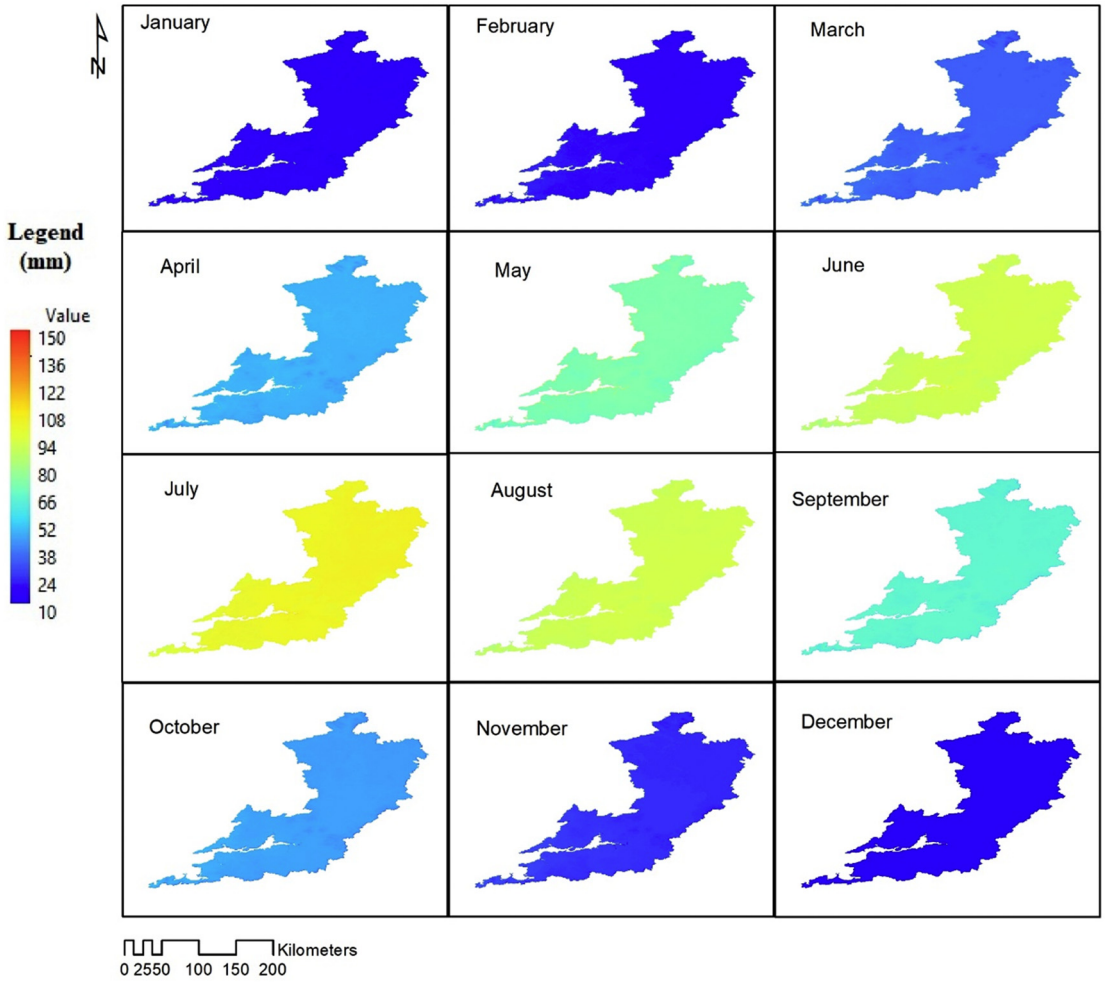


Fig. 12. Thornthwaite baseline monthly PETS raster maps.

the Shannon River Basin District was created for each month of the year. These rasters depict the long-term mean monthly PETS throughout the region in mm. The raster maps created are presented below.

- Blaney-Criddle

The Blaney-Criddle method estimates PETS based on mean monthly temperature and sunshine hours; rasters created using this approach are shown in Fig. 8. Fig. 8 shows that in general a significant increase in the PETS occurs in July. The simulated spatially distributed pattern of PETS using Blaney-Criddle has a significant change over the different maps shown in Fig. 8.

- Kharrufa

Similarly, to the Blaney-Criddle approach, the Kharrufa method uses mean monthly temperature and sunshine hours to estimate PETS; raster maps created by means of this approach are presented in Fig. 9. Fig. 9 shows that Karrufa method produces almost the same spatially distributed patterns of PETS using Blaney-Criddle over all the simulated months.

- Hargreaves and Samani

This approach represents one of the most complex applied during this study, requiring a minimum, maximum and mean temperature data as well as extra-terrestrial radiation. Raster map created using this approach are presented in Fig. 10.

Fig. 10 shows that Hargreaves and Samani method has almost the same spatially distributed patterns shown on all the simulated PETS maps except for December, January and February, their spatially distributed patterns have significant differences from others. Hargreaves and Samani method provides good spatially distributed estimations for the PETS. In general, this method fails to estimate the hot spot areas in terms of both the locations and the values. Hargreaves and Samani provides over estimated values in most of the eastern parts of the catchment and less estimated PETS values for the western part of the catchment.

- Oudin

The equation presented by Oudin also requires extra-terrestrial radiation data, however unlike the Hargreaves and Samani only mean monthly temperature is required. Raster maps prepared using this method are shown in Fig. 11. Oudin method provides very good spatially distributed estimations for the PETS. In general, this method provides good estimates for the hot spot areas in terms of both the locations and the values. Oudin provides over estimated values in the southern part of the catchment, which is mainly due to the location on the coastal areas.

- Thornthwaite

The Thornthwaite method uses mean monthly temperature to estimate both a radiation term and PETS; raster maps are presented in

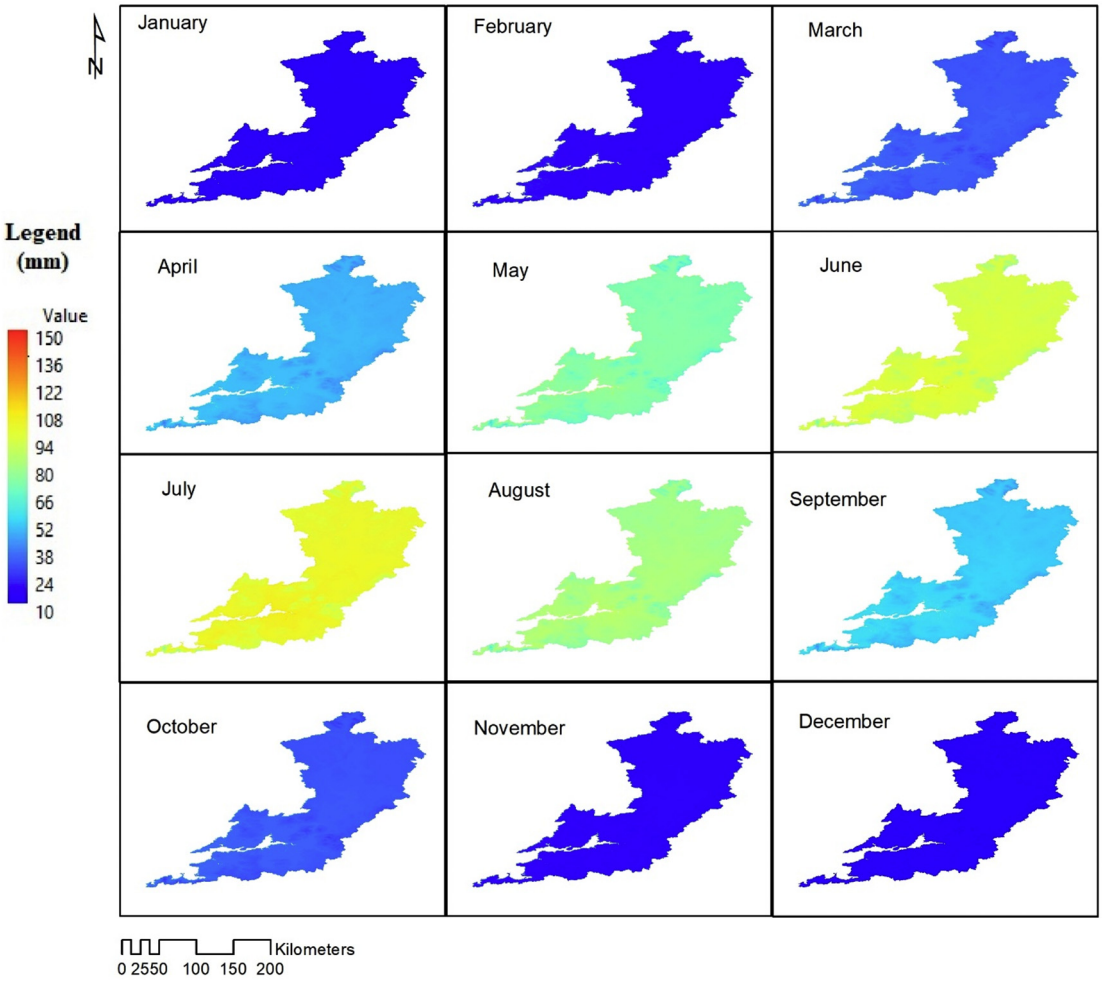


Fig. 13. Hamon baseline monthly PETS raster maps.

Fig. 12. Thornthwaite method has the lowest simulated PETS values for September, October and November with unique spatially distributed patterns for all of them compared with the other used methods, see Fig. 12.

- Hamon

PETS is estimated based on mean temperature, which is used to calculate a vapor density term, and daylight hours; raster maps created are presented in Fig. 13. Hamon method appears to be the most consistent method to simulate the PETS between summer and winter. This method has almost one spatially distributed PETS pattern for summer months and another different one for winter months.

Each empirical method applied successfully produced a spatially distributed estimation of long-term mean monthly PETS for the Shannon River Basin District. From initial inspection of the results, each method appears to produce reasonable estimates of PETS throughout the region; with minimal PETS rates during cold winter months and higher rates (up to 100+ mm per month) during summer months. In addition, a clear variation in PETS is visible in coastal areas in the southwest of the region which would be expected. However, from inspecting the raster maps produced it was not possible to determine the most accurate method for use within the Shannon River Basin District. Thus, further evaluation of the methods was necessary and is discussed in the following section. Figs. 14–15 show the seasonally comparison between the simulation methods for the baseline period.

3.2. Validation and performance evaluation

The modeled values in this study were evaluated against the secured Penman-Monteith PETS values of the four Met Éireann synoptic stations, based on a number of statistical values, which are R^2, RMSE, MAPE and MAD. These statistical values were calculated for each of the four locations and a mean value was taken for each, which shown in Fig. 16. Evaluation of Blaney-Criddle modeled PETS values is presented in Fig. 16 below. From the results, there is a clear disparity between the datasets at all four locations. This is further demonstrated by the low R^2 and high RMSE, MAPE and MAD values.

Similarly, results from the Kharrufa method are evaluated in Fig. 16 below. Although a more simplified approach the Kharrufa method returned somewhat more accurate results with a mean $R^2 = 0.652$, RMSE = 28.5 mm, MAPE = 51.5% and MAD = 20.9 mm.

Given the relative complexity of the Hargreaves and Samani method, one would have the expectation that the method would return somewhat accurate results. As it can be seen from Fig. 16 the modeled results are significantly more accurate the previous methods with a mean $R^2 = 0.774$, RMSE = 15.3 mm, MAPE = 24.8% and MAD = 11.8 mm.

Similarly to the Hargreaves and Samani method, the Oudin method also produced significantly improved estimates compared to the preceding methods as shown in Fig. 16, with a mean $R^2 = 0.860$, RMSE = 10.1 mm, MAPE = 18.6% and MAD = 7.7 mm. Similarly, given the relative complexity of the Thornthwaite method, one would have the expectation of more accurate estimates of PETS compared to some of the most simple methods. As it can be seen from Fig. 16 it did return relatively accurate results with a mean $R^2 = 0.841$, RMSE = 12.7 mm, MAPE = 33.3% and MAD = 9.2 mm. Finally, results of the Hamon method are presented in Fig. 16. The fact that the Hamon method may be considered one of the more simple methods applied as part of this study it returned the best mean $R^2 = 0.888$, RMSE = 8.6 mm, MAPE = 16.5% and MAD = 6.5 mm. In order to more clearly delineate the deviance between modeled and Met Éireann values, monthly PETS values

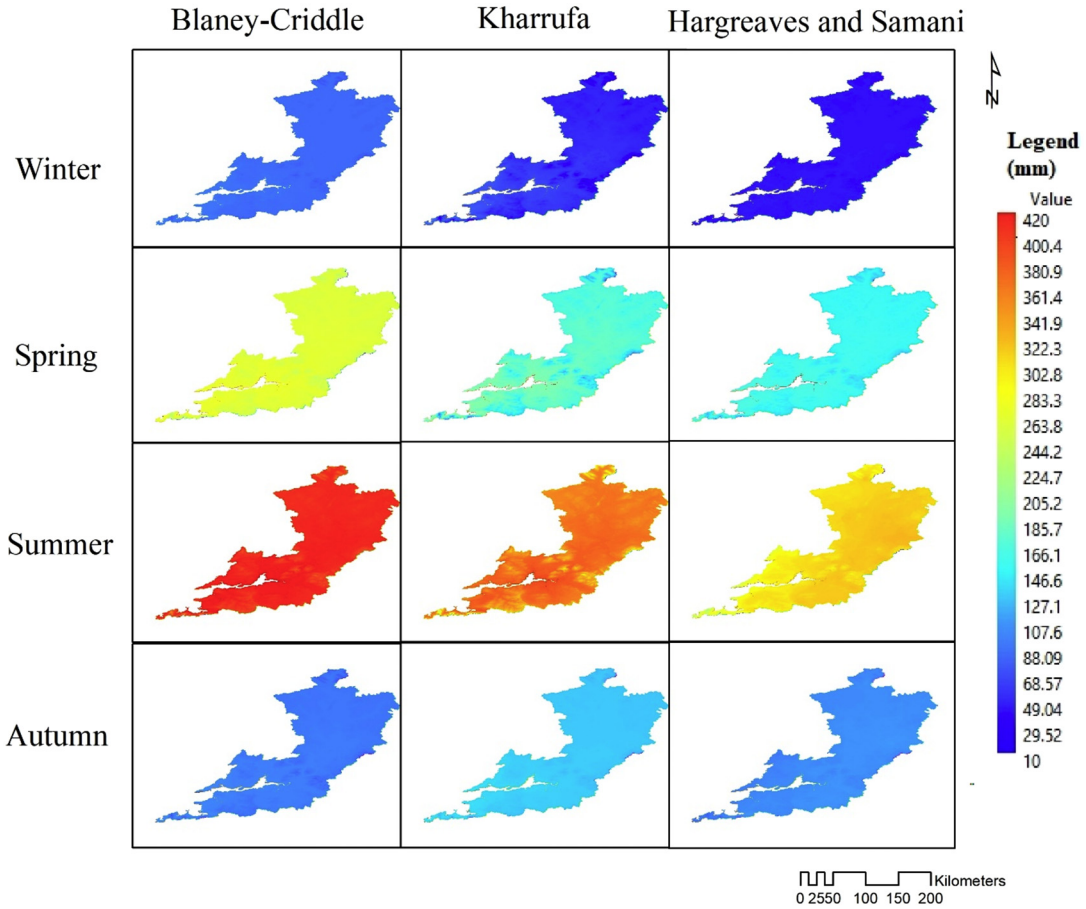


Fig. 14. Comparisons between the seasonally simulated baseline PETS raster maps (Blaney-Criddle, Kharrufa and Hargreaves and Samani).

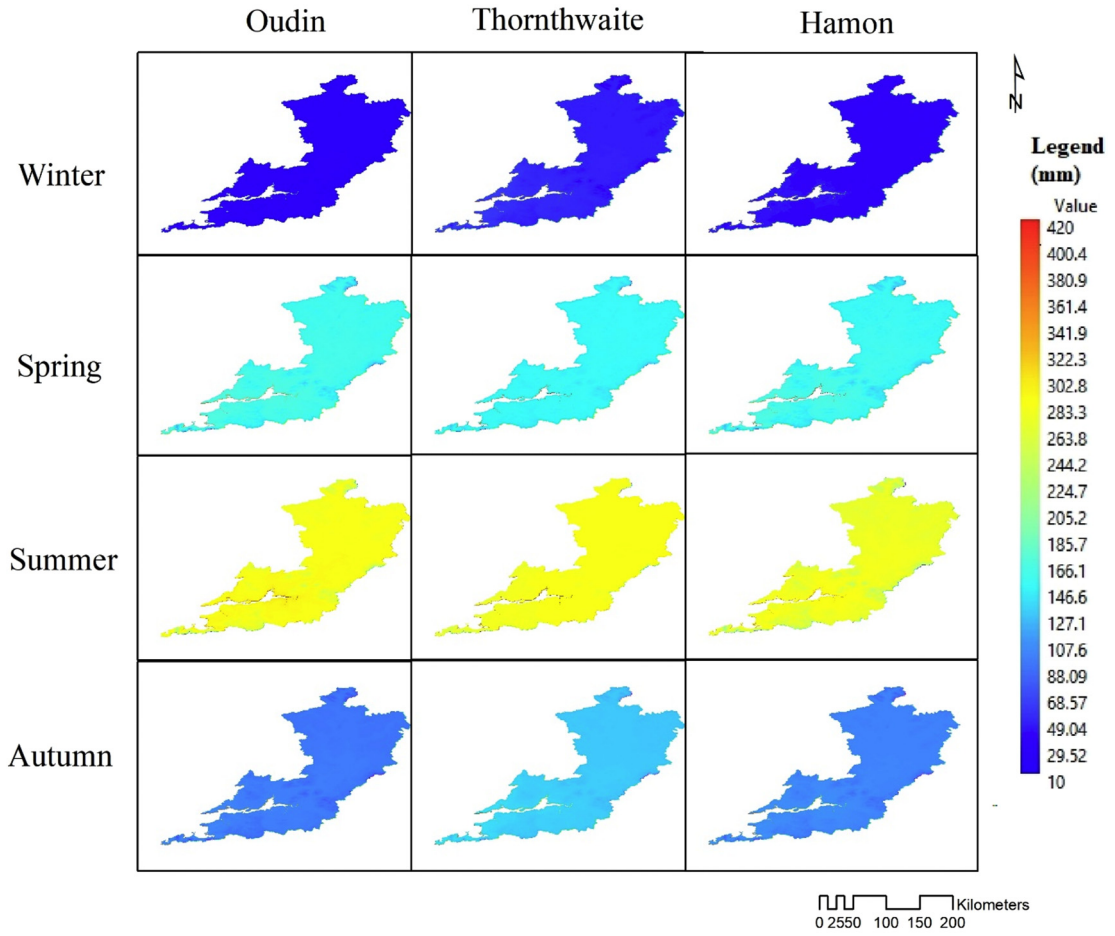


Fig. 15. Comparisons between the seasonally simulated baseline PETS raster maps (Oudin, Thornthwaite and Hamon).

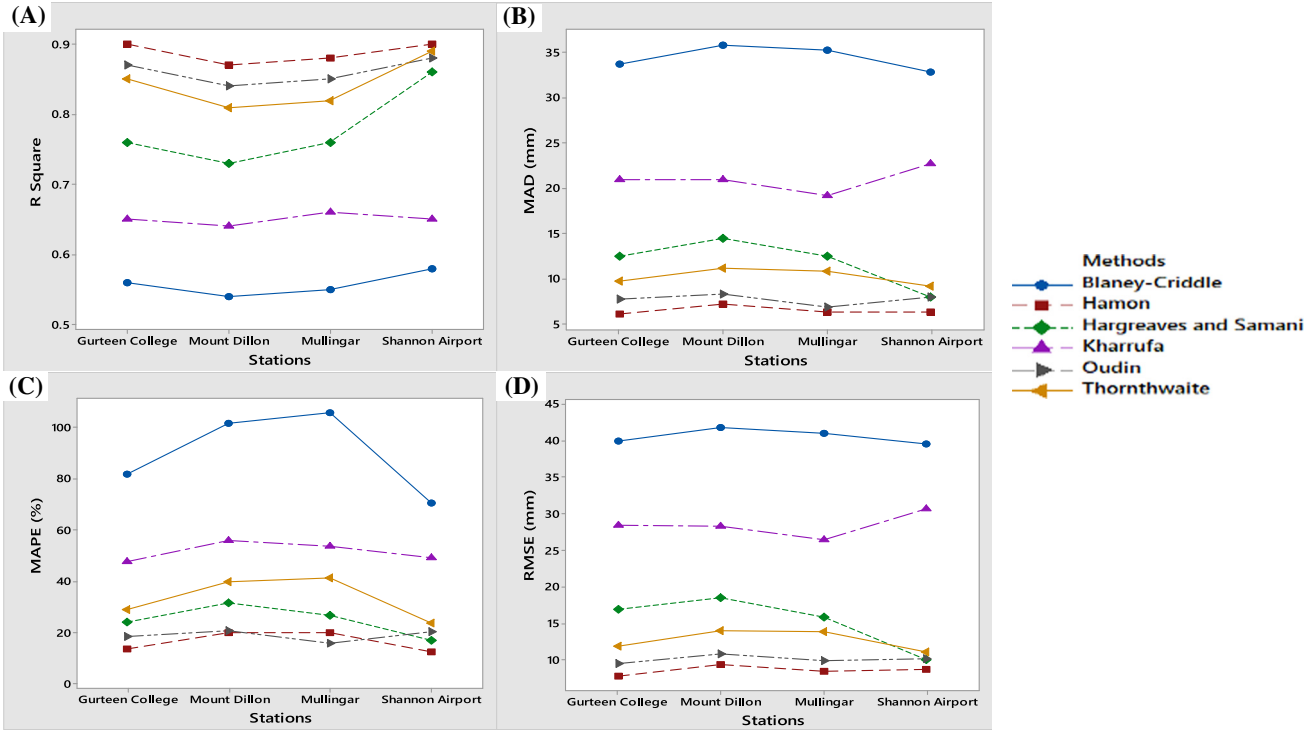


Fig. 16. Statistical parameters for performance evaluation process of each simulated method for the four synoptic stations. (A) R^2, (B) MAD(mm), (C) MAPE (%) and (D) RMSE(MM).

were plotted for each location and are provided in Fig. 17. From the figure, it is evident that, particularly during summer months (April–September), the PETS models consistently overestimate PETS. That might be because all the methods are not calibrated against the Irish summer long daytime and calibrating them was not possible due to the lack of observed evapotranspiration data. This overestimation is not really significant, so the validated methods can still be used in the Irish environment. During winter months (October–March) modeled results correspond more closely with the Met Éireann values, although it must also be considered that during this period PETS rates are at their lowest. Through the evaluation of the statistical results presented in Fig. 16 and examination of Fig. 17 the Hamon method was selected as the most appropriate method for application within the Shannon River Basin District and thus was selected for application in the final stage of this study, the results of which are presented within the following section. It could be concluded that Hamon method was performing the best for the Shannon catchment because of the simple parameterization which includes two main factors, the daytime period and the temperature, with an exponential relation which is one of the main deference between Hamon and the other methods.

3.3. Future PETS simulations

The Hamon method was first applied to mean monthly temperature data from 2020 for the four modeled climate change scenarios. Given the uncertainty of future climate change, monthly PETS raster maps were aggregated to represent growing (April to September) and non-growing (October to March) seasons, herein termed summer and winter respectively. Seasonal raster maps for baseline and 2020 PETS projections are presented in Fig. 18. As can be seen, a summer and winter raster map was created for each scenario. In order to evaluate the effect of climate change on PETS under the scenarios considered, seasonal PETS values at the same four locations as previously have been compared with baseline values as shown in Table 3.

Similarly, to 2020, results for 2050 are shown in Fig. 19 and Table 4.

Finally, results for 2080 scenarios are presented in Fig. 20 and Table 5.

The results present evidence that the modeled climate change scenarios would have a significant impact on future PETS rates within the Shannon River Basin District. In all locations, all scenarios predicted an increase in PETS for each future time interval.

4. Discussion

Empirical PETS equations are most suited to the regions within which they are developed; consequently, one would expect disparity between results for different methods for given conditions. From the results, it can be seen that there exists significant deviation between modeled results of up to 61.9 mm per month (Blaney-Criddle/Hamon in July at Mount Dillon), which means that each method simulates statistically significant deferent results from the other methods and there were no single pair of methods that can produce statistically significant similar PETS estimates. Also, it can be seen that the Blaney-Criddle, Kharrufa, and Hargreaves and Samani methods consistently overestimate PETS and with their large mean RMSE values of 40.6 mm, 28.5 mm and 15.3 mm respectively, they were concluded as unsuitable

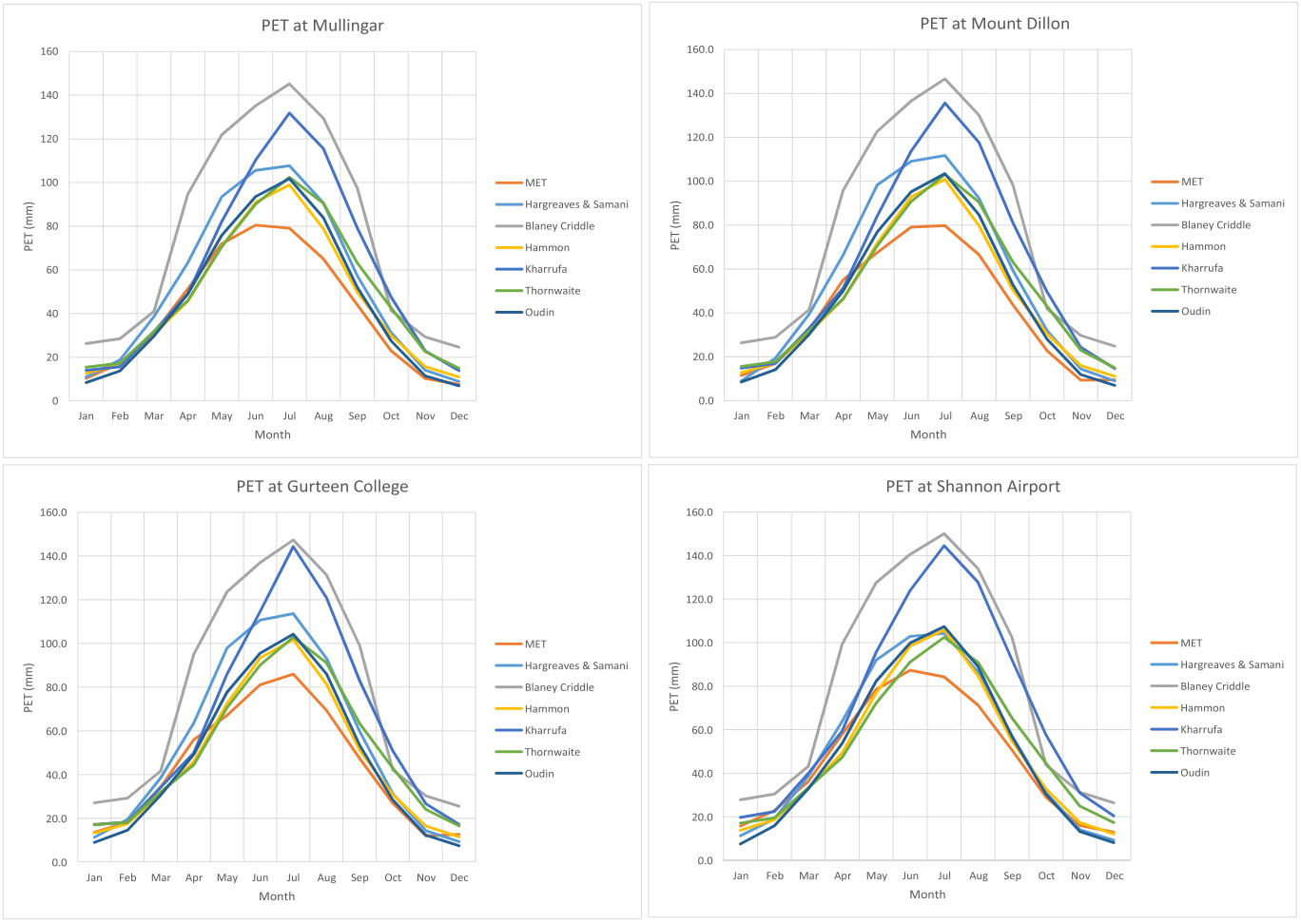


Fig. 17. Met Éireann and modeled monthly PETS at four synoptic stations located in the Shannon River Basin District.

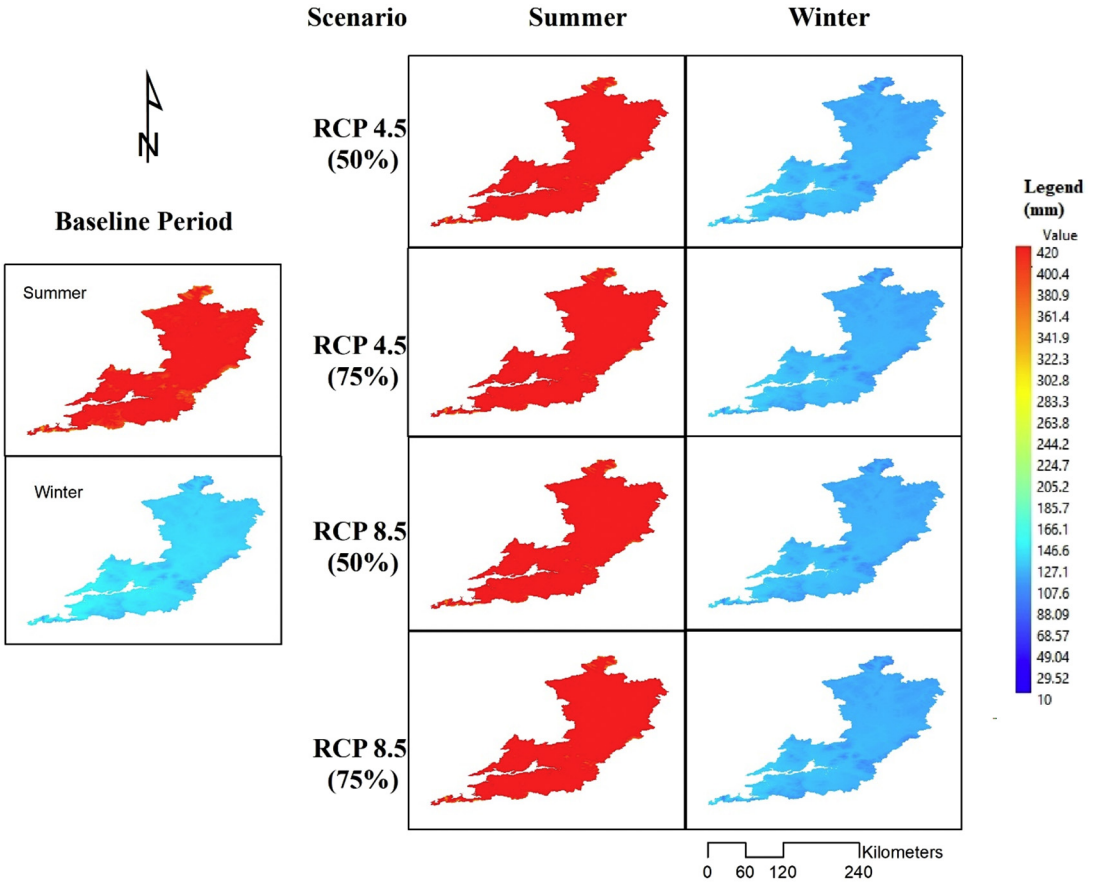


Fig. 18. Seasonal PETS baseline and projections for 2020 according to different Representative Concentration Pathways.

for application within the Shannon River Basin District and excluded from further evaluation. As can be seen, the remaining three methods consistently returned relatively similar results and in addition, although the Penman-Monteith may be the most reliable method, the Met Éireann PETS values are also subject to error making it difficult to ascertain the most accurate model. Yoder et al. (2005) compared lysimeter data with the Penman-Monteith method in a wet/humid region in the south-eastern United States similar to conditions prevailing in Ireland and found an R^2 of 0.91 with an error of 0.31 mm/day. Given this error it is possible to accumulate a total error of 9.3 mm in a 30 day period (Yoder et al., 2005). From Figs. 16–17, it can be seen the presence of such an error could have a significant impact on the relative accuracy of the Oudin, Thornthwaite and Hamon Methods. As can be seen, there exists a substantial spatial variation in PETS for a given period (in excess of 35 mm for July). Variations in excess of 20 mm exist between Oak Park Co. Carlow and Johnstown Castle Co. Wexford for July, which are sited approximately 70 km apart, see Fig. 1 for the locations. This represents approximately 33% of that measured at Oak Park. When Fig. 21 is compared with Fig. 17, it can be seen that values of PETS calculated using the Hamon method for all locations correlate reasonably well with the trends of measured values. While this does not validate the application of the Hamon method, it does demonstrate the capacity of the formula to reasonably account for variations in PETS within the Irish climate.

Throughout the last 50 years, the global climate has been subjected to warming because of the continuous rise in the concentration of greenhouse gasses in the atmosphere, which can be largely attributed to human activities (Stocker et al., 2013). Numerous studies of climate

Table 3
Seasonal PETS Baseline and projections for 2020 at four synoptic stations located in the Shannon River Basin District.

	Baseline		50% delta RCP4.5		50% delta RCP8.5		75% delta RCP4.5		75% delta RCP8.5	
Location	Winter	Summer	Winter	Summer	Winter	Summer	Winter	Summer	Winter	Summer
Mullingar (Sy.S.1)	116.5	434.7	117.6	439.0	117.8	439.8	117.8	439.0	118.1	440.6
Mount Dillon (Sy.S.2)	118.6	442.1	119.6	446.0	119.8	446.7	119.8	446.0	120.0	447.8
Gurteen College (Sy.S.3)	121.2	446.3	122.2	450.6	122.4	451.1	122.4	450.6	122.7	452.3
Shannon Airport (Sy.S.4)	127.8	470.2	128.9	474.3	129.1	475.0	129.2	474.3	129.4	476.4
Mean	121.0	448.3	122.1	452.5	122.3	453.2	122.3	452.5	122.6	454.3
% change			0.9	0.9	1.0	1.1	1.1	0.9	1.3	1.3

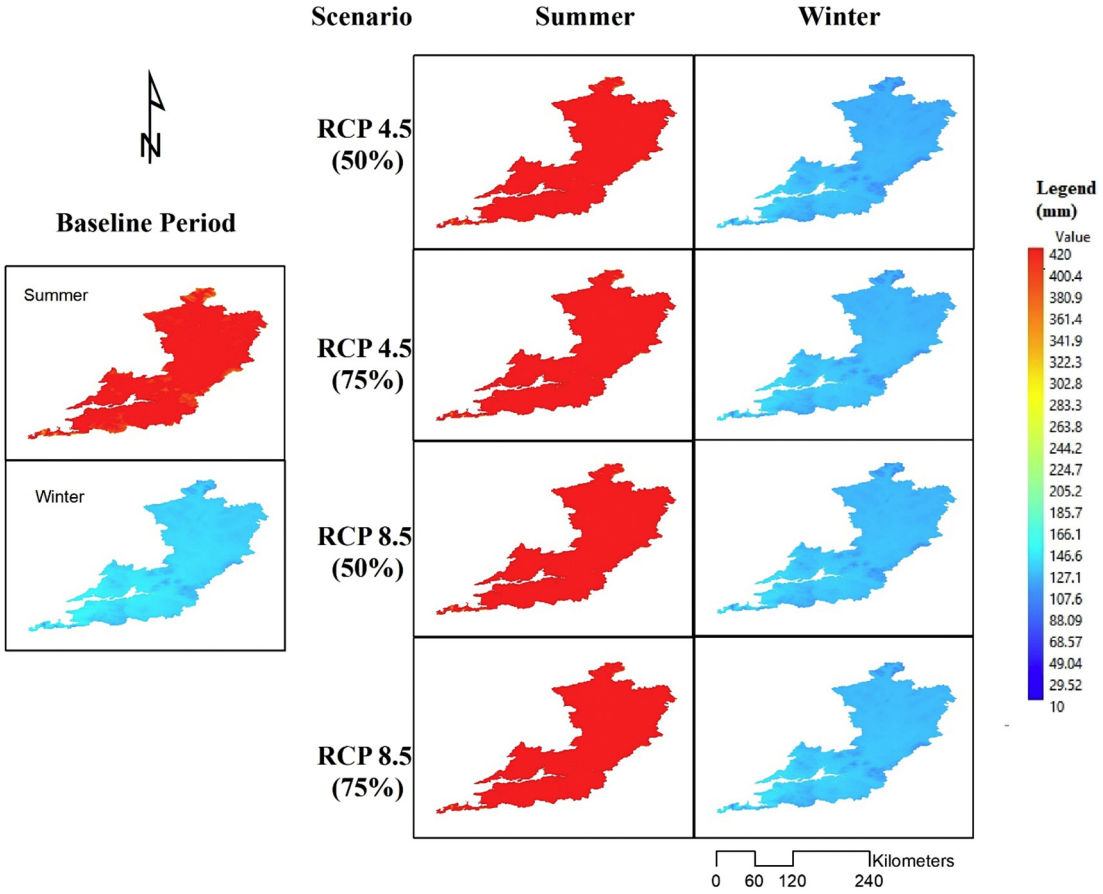


Fig. 19. Seasonal PETS baseline and projections for 2050 according to different Representative Concentration Pathways.

change have successfully revealed that the Earth's atmosphere is being altered by anthropogenic and biogenic emissions of carbon dioxide, other radioactively active gasses and aerosol precursors such as Sulphur dioxide (Chattopadhyay and Hulme, 1997). Global climate change is influencing the hydrological cycle by shifting rates of precipitation, recharge, discharge, and ET. To give an example of possible future scenarios; decreased precipitation during winter months to recharge groundwater storage within the Shannon River Basin District could exacerbate problems caused by reduced summer precipitation and increased ET rates. Consequently, reduced storage would result in less water being available during the drier summer months to sustain low flows and could result in water shortages. PETS was spatially modeled within the Shannon River Basin District for three future time intervals (2020, 2050 and 2080) using the Hamon method. For each time interval, data from four climate change scenarios were modeled in an attempt to take consideration of the indefinite nature of future climate change. A clear trend is evident in the results, where PETS is continuously increasing as a result of climate change from 0.9%–1.3% in 2020 up to 13.5% in 2080. A similar trend was discovered by (Scheff and Frierson, 2014), who modeled the effect of the warming of the earth's climate as a result of greenhouse gas pollution on PETS over the 21st century and found that variations in annual-mean PETS over the upcoming century are almost always positive. In order to better illustrate the fluctuations found in this study, Fig. 22 displays the mean seasonal deviation of PETS for each scenario considered. This figure further exhibits the increasing trend of PETS in the future, which may significantly affect water resources and availability in the Shannon River Basin District.

Table 4
Seasonal PETS Baseline and projections for 2050 at four synoptic stations located in the Shannon River Basin District.

	Baseline		50% delta RCP4.5		50% delta RCP8.5		75% delta RCP4.5		75% delta RCP8.5	
Location	Winter	Summer	Winter	Summer	Winter	Summer	Winter	Summer	Winter	Summer
Mullingar (Sy.S.1)	116.5	434.7	120.5	452.0	122.6	460.5	121.3	450.7	123.8	464.9
Mount Dillon (Sy.S.2)	118.6	442.1	122.4	459.2	124.5	465.5	123.1	460.1	125.5	469.9
Gurteen College (Sy.S.3)	121.2	446.3	125.3	467.9	127.6	472.6	126.2	470.0	128.9	478.0
Shannon Airport (Sy.S.4)	127.8	470.2	132.0	474.8	134.3	494.2	132.9	486.8	135.6	496.0
Mean	121.0	448.3	125.1	463.5	127.3	473.2	125.9	466.9	128.5	477.2
% change			3.3	3.4	5.1	5.5	4.0	4.1	6.1	6.4

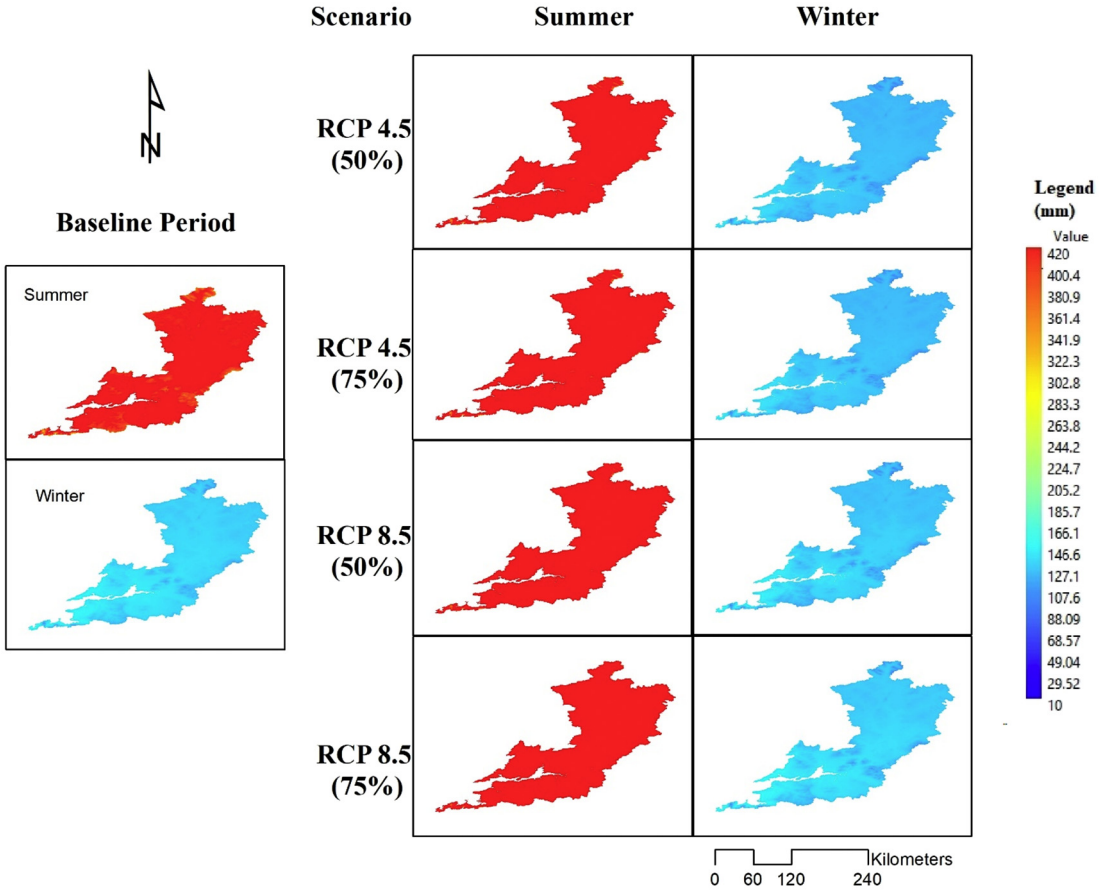


Fig. 20. Seasonal PETS baseline and projections for 2080 according to different Representative concentration pathways.

5. Conclusions

Evapotranspiration integrates energy and mass transfer between the Earth's surface and atmosphere and is the most active mechanism linking the atmosphere, hydrosphsophere, lithosphere and biosphere, it is responsible for monitoring atmospheric moisture and temperature. This study aimed to spatially estimate PETS, a complex hydrological process, within Ireland's Shannon River Basin District using GIS-based algorithms. The ability to accurately determine PETS is of critical importance in resource evaluation and sustainable water resource management policies as well as a host of hydrological and agricultural studies. Because of its complexity, and inherent spatial variability, PETS is particularly difficult to determine for a given location. From the selection of possible approaches, the use of empirical PETS formulae which integrate empirical constants and meteorological data were selected as the most appropriate method. Compared to more complex methods these relatively simple formulae require data which is monitored at a greater number of locations within the region, thus providing a more reliable spatial distribution of data. For example, temperature data which was used in this study was taken from 96 monitoring stations whereas more complex methods would require a host of variables some of which may only be measured at the four synoptic weather stations within the region or not at all. In this study, based on the availability of data, the complexity of formulae and their appropriateness for application within a GIS a number of methods were shortlisted.

Six temperature based methods were selected which would allow for the most appropriate to be identified. The 6 selected methods were applied within a GIS and each successfully produced long-term

Table 5
Seasonal PETS Baseline and projections for 2080 at four synoptic stations located in the Shannon River Basin District.

	Baseline		50% delta RCP4.5		50% delta RCP8.5		75% delta RCP4.5		75% delta RCP8.5	
Location	Winter	Summer	Winter	Summer	Winter	Summer	Winter	Summer	Winter	Summer
Mullingar (Sy.S.1)	116.5	434.7	122.3	458.4	129.0	458.4	123.4	456.5	131.4	497.0
Mount Dillon (Sy.S.2)	118.6	442.1	124.2	463.5	130.7	463.5	125.2	466.0	132.9	500.9
Gurteen College (Sy.S.3)	121.2	446.3	127.2	470.1	134.5	470.1	128.5	477.2	137.3	510.1
Shannon Airport (Sy.S.4)	127.8	470.2	133.9	490.0	141.1	492.1	135.2	492.5	143.8	527.9
Mean	121.0	448.3	126.9	470.5	133.8	471.0	128.1	473.1	136.4	509.0
% change			4.9	4.9	10.6	5.1	5.8	5.5	12.7	13.5

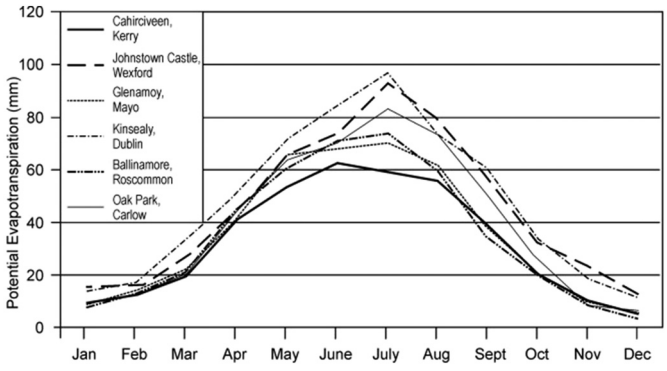


Fig. 21. Average monthly evapotranspiration measured at six lysimeters over the period 1971–1990 (Mills, 2000).

mean monthly PETS raster maps of the region. Through comparison with the Met Éireann data, the Hamon method was found to produce the most precise results with an RMSE of 8.6 mm. Each method applied in its own produced spatially distributed estimates of PETS. However, the Hamon method given its comparability to Met Éireann values and PETS trends was determined to be the most appropriate of the models tested and concluded to produce reasonable estimates of PETS within the Shannon River Basin District. It could be concluded that Hamon method was performing the best for the Shannon catchment because of the simple parameterization which includes two main factors, the daytime period and the temperature, with an exponential relation which is one of the main deference between Hamon and the other methods.

The Hamon method was therefore applied for three future time intervals (2020, 2050 and 2080) to study the effects of climate change. Four possible climate change scenarios were considered and associated future temperature for these scenarios was available through the downscaling results from (Gharbia et al., 2016b). The results present evidence

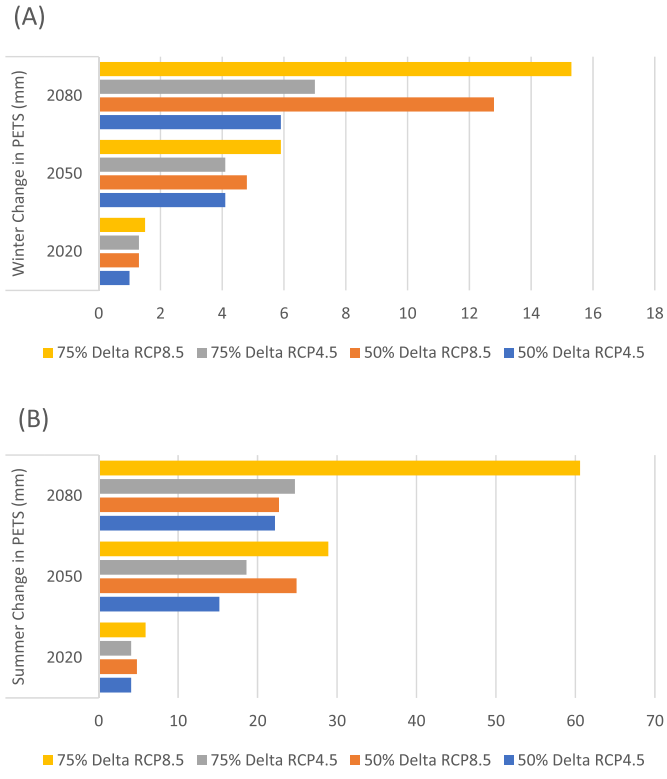


Fig. 22. Mean deviation of future seasonal PETS from baseline results for four climate change scenarios. (A) Winter season, (B) Summer season.

that the modeled climate change scenarios would have a significant impact on future PETS rates within the Shannon River Basin District. At all locations, all scenarios predicted an increase in PETS for each future time interval. The scale of increases in PETS was found to vary depending on climate change scenario and year. The maximum mean increase in PETS was as a result of the 75% RCP 8.5 scenario in 2080 which returned an increase of 75.9 mm annually. A clear trend is evident in this study, where PETS is continuously increasing as a result of climate change from 0.9%–1.3% in 2020 up to 13.5% in 2080. The calculated mean seasonal deviations of projected PETS from the baseline have significantly shown the increase in the PETS rates and trends for each scenario considered, which may significantly affect water resources and availability in the Shannon River Basin District. For future related research, the same process and algorithms should be applied on other catchments in different climatic zones which allows the validate the process in the different climates.

Acknowledgments

This research was funded jointly by Trinity College, Dublin through the Postgraduate Ussher Fellowship Award and by iSCAPE (Improving Smart Control of Air Pollution in Europe) project, which is funded by the European Community's H2020 Programme (H2020-SC5-04-2015) under the Grant Agreement No. 689954.

References

Abtew, W., 1996. Evapotranspiration Measurements and Modeling for Three Wetland Systems in South Florida. Wiley Online Library.
Allen, R.G., 2000. Using the FAO-56 dual crop coefficient method over an irrigated region as part of an evapotranspiration intercomparison study. J. Hydrol. 229, 27–41.
Allen, R.G., Pruitt, W.O., 1986. Rational use of the FAO Blaney-Criddle formula. J. Irrig. Drain. Eng. 112, 139–155.
Allen, R.G., Pereira, L.S., Raes, D., Smith, M., 1998. Crop Evapotranspiration-Guidelines for Computing Crop Water Requirements-FAO Irrigation and Drainage Paper 56. 300. FAO, Rome (D05109).
Andréassian, V., 2004. Waters and forests: from historical controversy to scientific debate. J. Hydrol. 291, 1–27.
Andréassian, V., Perrin, C., Michel, C., 2004. Impact of imperfect potential evapotranspiration knowledge on the efficiency and parameters of watershed models. J. Hydrol. 286, 19–35.
Blaney, H.F., Criddle, W.D., 1950. Determining Water Requirements in Irrigated Area from Climatological Irrigation Data, US Department of Agriculture, Soil Conservation Service, Technical Paper No. 96, p. 48.
Blaney, H.F., Criddle, W.D., 1964. Determining water requirements for settling water disputes. Nat. Resour. J. 4, 29.
Chattopadhyay, N., Hulme, M., 1997. Evaporation and potential evapotranspiration in India under conditions of recent and future climate change. Agric. For. Meteorol. 87, 55–73.
De Bruin, H., 1983. A model for the Priestley-Taylor parameter α. J. Clim. Appl. Meteorol. 22, 572–578.
Droogers, P., Allen, R.G., 2002. Estimating reference evapotranspiration under inaccurate data conditions. Irrig. Drain. Syst. 16, 33–45.
Fennessey, N.M., Vogel, R.M., 1996. Regional models of potential evaporation and reference evapotranspiration for the northeast USA. J. Hydrol. 184, 337–354.
Gharbia, S.S., Gill, L., Johnston, P., Pilla, F., 2015a. GEO-CWB: a dynamic water balance tool for catchment water management. 5th International Multidisciplinary Conference on Hydrology and Ecology (HydroEco2015), At Vienna, Austria.
Gharbia, S.S., Gill, L., Johnston, P., Pilla, F., 2015b. Trans-boundary European river's long-term changes analysis for water level and streamflow regime. 42nd IAH Congress (AQUA2015), At Rome, Italy.
Gharbia, S.S., Alfatah, S.A., Gill, L., Johnston, P., Pilla, F., 2016a. Land use scenarios and projections simulation using an integrated GIS cellular automata algorithms. Modeling Earth Systems and Environment 2, 151.
Gharbia, S.S., Gill, L., Johnston, P., Pilla, F., 2016b. Multi-GCM ensembles performance for climate projection on a GIS platform. Modeling Earth Systems and Environment 2, 1–21.
Gharbia, S.S., Gill, L., Johnston, P., Pilla, F., 2016c. Using GIS based algorithms for GCMs' performance evaluation. 18th IEEE Mediterranean Electrotechnical Conference MELECON 2016. IEEE, Cyprus.
Gharbia, S.S., Johnston, P., Gill, L., Pilla, F., 2016d. Using GIS based algorithms for GCMs' performance evaluation. Strategies 2, 3.
Gordon, D.R., 1998. Effects of invasive, non-indigenous plant species on ecosystem processes: lessons from Florida. Ecol. Appl. 8, 975–989.
Hamon, W.R., 1961. Estimating potential evapotranspiration. J. Hydraul. Div. 87, 107–120.
Hargreaves, G.H., 1975. Moisture availability and crop production. Trans. ASAE 18 (5), 980–984.

Hargreaves, G.H., Samani, Z.A., 1982. Estimating potential evapotranspiration. J. Irrig. Drain. Div. 108, 225–230.
Hargreaves, G.H., Samani, Z.A., 1985. Reference crop evapotranspiration from temperature. Appl. Eng. Agric. 1, 96–99.
Holdridge, L.R., 1959. Simple method for determining potential evapotranspiration from temperature data. Science 130, 572.
Holland, W.R., 1978. The role of mesoscale eddies in the general circulation of the ocean-numerical experiments using a wind-driven quasi-geostrophic model. J. Phys. Oceanogr. 8, 363–392.
Jensen, M.E., Burman, R.D., Allen, R.G., 1990. Evapotranspiration and Irrigation Water Requirements. ASCE Manuals and Reports on Engineering Practice No. 70. Am. Soc. Civil Engr., New York, NY 332 pp.
Kay, A., Davies, H., 2008. Calculating potential evaporation from climate model data: a source of uncertainty for hydrological climate change impacts. J. Hydrol. 358, 221–239.
Kharrufa, N., 1985. Simplified equation for evapotranspiration in arid regions. Beiträge zur Hydrologie 5, 39–47.
Kite, G.W., Droogers, P., 2000. Comparing evapotranspiration estimates from satellites, hydrological models and field data. J. Hydrol. 229, 3–18.
Linacre, E.T., 1977. A simple formula for estimating evaporation rates in various climates, using temperature data alone. Agric. Meteorol. 18, 409–424.
Liu, Y., Phinn, S.R., 2003. Modelling urban development with cellular automata incorporating fuzzy-set approaches. Comput. Environ. Urban. Syst. 27, 637–658.
Makkink, G., 1957. Testing the Penman formula by means of lysimeters. J. Inst. Water Eng 11, 277–288.
Mcguinness, J.L., Bordne, E.F., 1972. A Comparison of Lysimeter-Derived Potential Evapotranspiration With Computed Values. US Dept. of Agriculture.
Mills, G., 2000. Modelling the water budget of Ireland—evapotranspiration and soil moisture. Ir. Geogr. 33, 99–116.
Oudin, L., Hervieu, F., Michel, C., Perrin, C., Andréassian, V., Anctil, F., Loumagne, C., 2005. Which potential evapotranspiration input for a lumped rainfall–runoff model?: part 2—towards a simple and efficient potential evapotranspiration model for rainfall–runoff modelling. J. Hydrol. 303, 290–306.
Oudin, L., Moulin, L., Bendjoudi, H., Ribstein, P., 2010. Estimating potential evapotranspiration without continuous daily data: possible errors and impact on water balance simulations. Hydrol. Sci. J. 55, 209–222.
Parmele, L., McGuinness, J., 1974. Comparisons of measured and estimated daily potential evapotranspiration in a humid region. J. Hydrol. 22, 239–251.
Penman, H.L., 1948. Natural evaporation from open water, bare soil and grass. Proceedings of the Royal Society of London A: Mathematical, Physical and Engineering Sciences. The Royal Society, pp. 120–145.
Portugali, J., Izak, B., Izak, O., 1994. Geogr. Anal. 26, 321.
Pruitt, W., Doorenbos, J., 1977. Empirical Calibration: A Requisite for Evapotranspiration Formulae Based on Daily or Longer Mean Climate Data? The Committee
Romanenko, P., 1973. Effect of a Transverse Mass Flow on Heat Transfer and Dynamics of a Turbulent Hot Air Flow in Axi Symmetric Diffusor with a Permeable Wall (DTIC Document).
Rosenzweig, M.L., 1968. Net primary productivity of terrestrial communities: prediction from climatological data. Am. Nat. 67–74.
Scheff, J., Frierson, D.M., 2014. Scaling potential evapotranspiration with greenhouse warming. J. Clim. 27, 1539–1558.
Shukla, J., Mintz, Y., 1982. Influence of land-surface evapotranspiration on the earth's climate. Science 215, 1498–1501.
Singh, V., Xu, C., 1997. Evaluation and generalization of 13 mass-transfer equations for determining free water evaporation. Hydrol. Process. 11, 311–323.
Stocker, T.F., Qin, D., Plattner, G., Tignor, M., Allen, S., Boschung, J., Nauels, A., Xia, Y., Bex, V., Midgley, P., 2013. Climate Change 2013: The Physical Science Basis. Intergovernmental Panel on Climate Change, Working Group I Contribution to the IPCC Fifth Assessment Report (AR5). Cambridge University Press, New York.
Swenson, S., Wahr, J., 2006. Estimating large-scale precipitation minus evapotranspiration from GRACE satellite gravity measurements. J. Hydrometeorol. 7, 252–270.
Thornthwaite, C.W., 1948. An approach toward a rational classification of climate. Geogr. Rev. 38, 55–94.
Thornthwaite, C.W., Mather, J.R., 1957. Instructions and Tables for Computing Potential Evapotranspiration and the Water Balance.
Turc, L., 1961. Estimation of irrigation water requirements, potential evapotranspiration: a simple climatic formula evolved up to date. Ann Agron 12, 13–49.
Wilson, K.B., Hanson, P.J., Mulholland, P.J., Baldocchi, D.D., Wullschleger, S.D., 2001. A comparison of methods for determining forest evapotranspiration and its components: sap-flow, soil water budget, eddy covariance and catchment water balance. Agric. For. Meteorol. 106, 153–168.
Wu, F., 2002. Calibration of stochastic cellular automata: the application to rural-urban land conversions. Int. J. Geogr. Inf. Sci. 16, 795–818.
Xu, C., Singh, V., 2000. Evaluation and generalization of radiation-based methods for calculating evaporation. Hydrol. Process. 14, 339–349.
Xu, C.Y., Singh, V., 2001. Evaluation and generalization of temperature-based methods for calculating evaporation. Hydrol. Process. 15, 305–319.
Xu, C.-Y., Singh, V., 2002. Cross comparison of empirical equations for calculating potential evapotranspiration with data from Switzerland. Water Resour. Manag. 16, 197–219.
Yoder, R., Odhiambo, L., Wright, W., 2005. Evaluation of methods for estimating daily reference crop evapotranspiration at a site in the humid southeast United States. Appl. Eng. Agric. 21, 197–202.
Zhang, L., Dawes, W., Walker, G., 2001. Response of mean annual evapotranspiration to vegetation changes at catchment scale. Water Resour. Res. 37, 701–708.
Zhao, C., Feng, Z., Chen, G., 2004. Soil water balance simulation of alfalfa (*Medicago sativa* L.) in the semiarid Chinese Loess Plateau. Agric. Water Manag. 69, 101–114.